ESSAYS ON INVESTOR SENTIMENT AND INSTITUTIONAL TRADING MOMENTUM

by

James Gerard Bulsiewicz

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STATEMENT OF DISSERTATION APPROVAL

The dissertation of **James Gerard Bulsiewicz**

has been approved by the following supervisory committee members:

Michael Cooper	, Chair	**04/30/2015** Date Approved
Elena Asparouhova	, Member	**04/30/2015** Date Approved
Hendrik Bessembinder	, Member	**04/30/2015** Date Approved
Marlene Plumlee	, Member	**04/30/2015** Date Approved
Jingyi Zhu	, Member	**04/30/2015** Date Approved

and by **William Hesterley** , Chair/Dean of

the Department/College/School of **David Eccles School of Business**

and by David B. Kieda, Dean of The Graduate School.

ABSTRACT

This dissertation is composed of 3 chapters on the topics of investor sentiment and institutional trading momentum. In the first chapter, I investigate whether the returns to cross-sectional anomalies reported in the finance literature are due to investor sentiment. I present evidence of a weak relation between cross-sectional anomalies and investor sentiment. Using a larger collection of cross-sectional anomalies, I find that only a small subsample of these anomalies exhibits a relation with investor sentiment. This result does not appear to be due to certain anomalies being more sensitive to changes in macroeconomic conditions. Further I show that the predictive power of sentiment diminishes significantly after controlling for the Fama and French factors. These results suggest that the returns to active trading strategies are generally not due to sentiment-driven mispricing. In the second chapter, I investigate whether the relation between investor sentiment and cross-sectional anomalies is due to short sale constraints. I find that the average security in these strategies is not hard-to-short. Furthermore, the short leg does not appear to be harder to short or more overvalued than the long leg. However, I find that these strategies are more illiquid and have higher institutional ownership following low sentiment. These results imply that the relation between investor sentiment and profitable trading strategies could be due to illiquidity and institutional trading, rather than short sale constraints. Finally, in the third chapter I investigate whether the collective trades of financial institutions create mispricing in the stock market. Previous studies have generally found a positive relation between institutional demand and short-term returns, consistent

with the interpretation that institutional trading pushes prices towards fundamental values. However, these studies do not control for the general and firm-specific trends in institutional ownership. After removing the trend in institutional ownership using the Hodrick-Prescott filter, I find strong evidence that financial institutions create substantial mispricing in the market. There is a large reversal in both returns and ownership following periods when ownership is abnormally high or low.

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CHAPTER 1

SAMPLE SELECTION AND THE RELATION BETWEEN INVESTOR SENTIMENT AND PROFITABLE TRADING STRATEGIES

Recent empirical evidence suggests that there are profitable trading opportunities in the stock market. A number of studies document trading strategies that have historically earned a positive return.[1] These studies suggest that an investor could earn a positive return by sorting firms on an observable variable and then investing in one extreme portfolio and selling the other extreme portfolio. (See Ang et al. (2006, 2009), Ball and Brown (1968), Banz (1981), Cooper, Gulen, Schill (2008), Jegadeesh and Titman (1993), Sloan (1996), etc.)

Some researchers provide evidence supporting the view that these strategies are compensation for risk (Ball, Sadka, and Sadka (2009), Fama and French (1992, 1993), Liew and Vassalou (2000), etc.) while other researchers present evidence implying that these strategies are due to mispricing (Bernard and Thomas (1989, 1990), Griffin and Lemmon (2002), Lakonishok, Shleifer, and Vishny (1994), etc.). However, there is not yet a consensus on whether the returns to these strategies are due to risk or mispricing.

A recent body of literature suggests that these trading strategies earn positive

[1] I define a trading strategy as the long-short portfolio which goes long on one portfolio of securities and sells short another portfolio of securities. Henceforth, I will refer to the return of the long-short portfolio as a trading strategy or more simply as a strategy.

returns because investors are unable or unwilling to make trades to eliminate the mispricing. Investors are not able to correct the mispricing when the costs of doing so are greater than the potential payoffs. Thus, there are limits of arbitrage (Lam and Wei (2011), Lewellen (2011), Shleifer and Vishny (1997)). In particular, a security could become overpriced if investors are not able to sell the security short, i.e., the security is hard-to-short. In a recent paper, Stambaugh, Yu, and Yuan (2012) examine whether certain trading strategies are profitable because these strategies invest in securities that are hard-to-short. They investigate returns to the long leg, short leg, and long-short portfolios for 16 different trading strategies following high and low investor sentiment periods and find results consistent with short sale limits to arbitrage. While they present convincing evidence regarding the 16 strategies they examine, it is not clear whether their results can be extended to all profitable trading strategies or are specific to the strategies that they tested.

Using the same tests employed in Stambaugh, Yu, and Yuan (2012) and a larger collection of trading strategies, I re-examine whether these strategies are profitable because these strategies take short positions in hard-to-short securities. I find much weaker evidence in support of the hard-to-short hypothesis. Based on the arguments presented in Stambaugh, Yu, and Yuan (2012), the long leg of each investment strategy should not have large return differences following high and low investor sentiment, while the short leg should have lower returns following high investor sentiment than following low investor sentiment. Additionally, each strategy should be more profitable following periods of high sentiment.[2]

[2] Stambaugh, Yu, and Yuan (2012) rely on Miller's (1977) reasoning that if a security is hard-to-short, it might become overvalued in the sense that it does not reflect the average market valuation because investors cannot make trades that would lead the security to a price that reflects this average valuation.

I test if the results reported in Stambaugh, Yu, and Yuan (2012) can be extended to 34 additional trading strategies. Consistent with their results, I find that the returns of the long leg portfolios are weakly affected by investor sentiment. Therefore, the long leg portfolio results presented in Stambaugh, Yu, and Yuan (2012) can be generalized to a larger collection of trading strategies. This implies that the returns to the long leg portfolios are not due to short sale constraints.

Next I test if the short leg of each strategy has a higher return following high investor sentiment than following low investor sentiment. However, unlike in Stambaugh, Yu, and Yuan (2012), I find that for a large number of trading strategies there is essentially no difference in returns for the short leg across periods of high versus low investor sentiment. Using the same tests used in Stambaugh, Yu, and Yuan (2012), I also find evidence that a large number of trading strategies are not more profitable following high investor sentiment. Typically, I find evidence consistent with the hard-to-short hypothesis for less than 40% of the trading strategies considered. This result is robust across 6 measures of investor sentiment.

Stambaugh, Yu, and Yuan (2012) find that the returns to a set of 16 trading strategies can be predicted using lagged investor sentiment. However, when I re-run the same tests using a larger collection of trading strategies I find that the majority of the

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Combining this argument with investor sentiment, they propose that firms are more likely to be overvalued following high investor sentiment when expectations are also high, than following low investor sentiment when expectations are lower. Using the preceding argument, Stambaugh, Yu, and Yuan (2012) reason that if a strategy is profitable primarily due to overpricing, the returns to this strategy should be larger following high investor sentiment than following low investor sentiment. Additionally, supposing that the securities in the long leg face the least amount of short sales constraints, these securities should not be greatly affected by investor sentiment, because if a security becomes over- or under-valued then this mispricing can be corrected by the market. On the other hand, supposing that the securities in the short leg face short sale constraints, then these securities are more likely to become overvalued when sentiment is high, leading these securities to have lower returns following high investor sentiment.

returns to these strategies cannot be predicted using lagged investor sentiment. I check the robustness of these results using 5 additional measures of investor sentiment and find similar results.

In a recent paper, Sibley et al. (2013) present evidence that investor sentiment is related to economic conditions. If this is the case, then the results presented in this paper could be due to the 34 additional trading strategies being less sensitive to macroeconomic conditions than the original 16 trading strategies. Yet, even after controlling for the portion of investor sentiment that is related to 13 macroeconomic variables, I still find a relation between investor sentiment and some of the original 16 trading strategies. Therefore, it appears that the results presented in this paper are not due to 1 group of strategies being more sensitive to economic conditions.

Recently, Huang et al. (2015) suggest that there is noise in the Baker and Wurgler (2006) investor sentiment measure. They propose a new investor sentiment measure that is supposed to contain less noise. I assess whether the prior results change using this new measure of investor sentiment. Prior to controlling for risk, I find that there is a strong relation between both the long leg and short leg portfolios, but this relation becomes weak after controlling for risk. Further, the use of this measure does not produce a strong relation between the long-short portfolios and investor sentiment. Therefore, it does not appear that my results are due to using a noisy measure of investor sentiment.

As a final robustness check, I simulate 10,000 long, short, and long-short portfolios. I find that only 10% of the long-short portfolios have a statistical relation with investor sentiment. Moreover, after removing the component of investor sentiment that is related to the economy, I find that there is little change in the percentage of strategies with a relation with investor sentiment. Thus, these results confirm the general finding of this paper: that there is a weak relation between profitable trading strategies and investor sentiment.

A common research question in finance is to ask why certain trading strategies earn a positive return. For example, Lesmond, Schill, and Zhou (2004) and Korajczyk and Sadka (2004) propose that trading on past price performance appears to be profitable because this strategy invests in securities with high transaction costs; likewise, Ng, Rusticus, and Verdi (2008) find that trading on earnings appears to be profitable because this strategy invests in securities with high transaction costs. On the other hand, some scholars propose an explanation that could be true for all profitable trading strategies, not just a subsample of profitable trading strategies (Stambaugh, Yu, and Yuan (2012)).

If a proposed explanation could be true for any profitable trading strategy, then it is desirable for studies evaluating the proposed explanation to include a broad cross section of strategies. Focusing on a small set of strategies is associated with reduced statistical power and potentially results in bias. In some research areas the researcher's population is well-defined and so the researcher can construct a sample that is representative of the population. Unfortunately, in finance the population of profitable trading strategies is not clearly defined. Financial scholars know the trading strategies reported in the literature that have historically yielded a positive return, but the literature may not have documented the entire population of profitable trading strategies in the market yet.

One solution to this problem is to lower the chance that the researcher will reject the null hypothesis when it is in fact true by increasing the sample size. For example, Stambaugh, Yu, and Yuan (2012) test the hard-to-short hypothesis using a sample of 16 profitable trading strategies. However, they do not consider a number of prominent trading strategies in the literature, including strategies that trade on firm idiosyncratic risk, analyst forecast dispersion, and positive or negative earnings announcements. Each of these strategies has historically yielded a positive return (see for example Ang et al. (2006, 2009), Diether, Malloy, and Scherbina (2002), Ball and Brown (1968), and Bernard and Thomas (1989, 1990)). Therefore, it is unclear whether the results reported in Stambaugh, Yu, and Yuan (2012) can be generalized to all trading strategies or if their results are sample specific. I address this potential deficiency.

In this paper, I contribute to the literature by presenting strong evidence that the returns to profitable trading strategies are not the result of those firms being hard-to-short. Generally, I find support for the hard-to-short hypothesis for less than 40% of the strategies considered, inclusive of those used in Stambaugh, Yu, and Yuan (2012). This result obtains both when I assess differences in returns between high and low investor sentiment states and when I assess the predictability of long-short portfolio returns using investor sentiment. In addition, I provide evidence that research on trading strategies is affected by the size and representativeness of the strategy sample. This finding could be important in other areas of finance, such as when studying initial public offerings or mergers and acquisitions.

The rest of the paper is organized as follows: Section 1.1 presents a brief literature review, Section 1.2 describes the data and methodology, Section 1.3 presents some results that are in contrast to those presented in the literature, and Section 1.4 concludes.

1.1 Literature Review

A growing body of literature that investigates investor sentiment and asset pricing. Antoniou, Doukas, and Subrahmanyam (2011) investigate investor sentiment and price momentum. They find that momentum profits only occur in optimistic periods and are strongest in poorly performing stocks. Similarly, Cooper, Gutierrez, and Hameed (2004) find that momentum is stronger following positive market returns than following negative market returns. Lee, Jiang, and Indro (2002) investigate whether sentiment is a priced risk factor using the Investors' Intelligence sentiment index as their measure of investor sentiment and find evidence that sentiment is a priced risk factor. In a related study, Beer, Watfa, and Zouaoui (2011) find that a portfolio of stocks with high exposure to sentiment outperforms a portfolio of stocks with low exposure to sentiment. Chang, Fuh, and Hsu (2008) and Bergman and Jenter (2005) investigate employee sentiment and employee stock options. Joseph, Wintoki, and Zhang (2011) measure investor sentiment as online search intensity defined as the number of times investors search for a particular firm ticker. They find that online search intensity predicts abnormal stock returns and trading volumes. Some scholars use mutual funds flows as a proxy for investor sentiment. Brown et al. (2005) use daily mutual fund flows as a proxy for investor sentiment in the United States and in Japan and find that investor sentiment is priced in both markets. Ben-Rephael, Kandel, and Wohl (2012) use aggregate net exchanges of equity funds as a measure of investor sentiment and find that this measure is positively related to aggregate stock market excess returns. Kim and Ha (2010) find that investor sentiment affects small cap, low price, and low book-to-market firms listed on the Korean stock exchange.

Another body of literature looks at accounting anomalies and investor sentiment.

Livnat and Petrovits (2009) investigate investor sentiment, post-earnings announcement drift, and accruals. They find that holding extreme good news firms or firms with low accruals following pessimistic sentiment periods outperforms holding similar firms following high sentiment periods. They conclude that investor sentiment influences earnings-based trading strategies. Kaplanski and Levy (2011) find that investor sentiment affects some analysts' recommendations. Hribar and McInnis (2012) find that investor sentiment affects analysts' earnings forecasts of hard-to-value firms. Seybert and Yang (2012) conclude that management earnings guidance helps the market to assess their earnings expectations and to adjust for sentiment-driven overvaluation.

Other researchers have investigated investor sentiment and stock market returns outside of the United States. Baker, Wurgler, and Yuan (2012) find that their global sentiment index and local stock market sentiment indices are negatively related to stock market returns; when sentiment is high, future returns are low on relatively difficult-to-arbitrage and difficult-to-value stocks. Hwang (2011) finds that a country's popularity among American investors influences their demand for those securities and this can lead the firms' share prices to move away from their fundamental values. Other papers construct sentiment-related models (Baker and Stein (2004) and Barberis, Shleifer, and Vishny (1998)). Additional sentiment-related papers include Edmans, Garcia, and Norli (2007), Kaplanski and Levy (2010), Karakatsani and Salmon (2007, 2008), Lemmon and Portniaguina (2006), and Tetlock (2007). Edmans, Garcia, and Norli (2007) investigate stock market returns following international soccer matches and whether a win or a loss affects market returns following a match. Kaplanski and Levy (2010) investigate how the market responds to aviation disasters. Karakatsani and Salmon (2007) investigate nonlinearities in the formation of institutional and individual sentiment while Karakatsani and Salmon (2008) investigate stock market returns and different sentiment states. Lemmon and Portniaguina (2006) find that investor sentiment predicts the returns of small stocks and stocks with low institutional ownership, but sentiment does not predict the value or momentum premiums. Tetlock (2007) investigates investor sentiment as proxied by the "Abreast of the Market" column in the *Wall Street Journal*, and finds that high media pessimism predicts downward pressure on market prices followed by a reversion to fundamentals, and unusually high or low pessimism predicts high market trading volume.

My research is most closely related to 4 papers: Baker and Wurgler (2006), Chung et al. (2012), Miller (1977), and Stambaugh, Yu, and Yuan (2012). Baker and Wurgler (2006) construct a new measure of investor sentiment and find evidence suggesting that hard-to-value and difficult-to-arbitrage securities are affected by investor sentiment. Baker and Wurgler (2006) also test whether investor sentiment predicts the returns of securities that they believe are hard-to-value. They find mixed results, but overall their results indicate that sentiment has an effect on hard-to-value and hard-to-arbitrage firms. Chung et al. (2012) build on the work by Baker and Wurgler (2006) by investigating whether investor sentiment has varying effects across different economic states. They run predictive regressions using the variables from Baker and Wurgler (2006) and Stambaugh, Yu, and Yuan (2012) and find that investor sentiment has higher predictive power during expansionary periods than during recessions.

Miller (1977) argues that if a stock is hard-to-short and there is heterogeneity in firm valuations, the share price will reflect the most optimistic valuation; however, if a stock is hard-to-short, investors will be able to sell short the stock so it reflects the average valuation in the market. Combining the work of Miller (1997) and Baker and Wurgler (2006), Stambaugh, Yu, and Yuan (2012) argue that if the securities in the short legs of each trading strategy are hard-to-short, then these stocks should follow the patterns implied by Miller (1977). Miller's (1977) argument implies that during high investor sentiment the securities that are hard-to-short will be overvalued; however, when investor sentiment is low valuations for hard-to-short securities will also be low and they will not be overvalued. On the other hand, securities that are easy-to-short should not be overvalued relative to the average valuation because investors can simply sell or short sell the stock if it becomes overvalued. Therefore, Stambaugh, Yu, and Yuan (2012) present 3 hypotheses based on Miller's (1977) argument. First, they hypothesize that each trading strategy should be stronger following high sentiment. Next, they hypothesize that the returns on the short-leg portfolio of each strategy should be lower when sentiment is high because these firms already reflect a high valuation. Finally, they hypothesize that investor sentiment should not significantly affect the returns of the long-leg portfolios. Their results are consistent with these hypotheses.

1.2 Data Description and Methodology

1.2.1 Data Description

Daily and monthly stock market data are taken from the Center for Research in Security Prices (CRSP) database. Accounting data at the quarterly and annual frequency are obtained from the COMPUSTAT database. Quarterly analysts' earnings forecasts and street-level actual earnings values are taken from the Institutional Brokers Estimates System (I/B/E/S) unadjusted actual and detail files. The CRSP, COMPUSTAT, and I/B/E/S datasets are all accessed via the Wharton Research Data Services (WRDS) website.

The Baker and Wurgler (2006) orthogonalized and raw investor sentiment indices and the 6 proxies for investor sentiment are kindly provided by Jeffrey Wurgler on his personal website. The University of Michigan Consumer sentiment index and the Consumer Price Index (CPI) are obtained from the Federal Reserve Bank of St. Louis website. The Fama and French (1993) 3 factors and the risk-free rate are generously provided by Kenneth French on his personal website.[3] Following Fama and French (1993) I define the risk-free rate as the 1-month Treasury bill rate.

1.2.2 Overview of 86 Different Trading Strategies

I consider a total of 86 different trading strategies covering 43 different financial variables. Of the 86 strategies, 84 are based on portfolios formed using single-variable sorts, while 2 of the strategies are combinations of a selection from these 84 strategies. Sometimes I have 2 or more strategies that trade on the same financial variable. This occurs if a variable has been defined in more than one way in the literature, if the definition given in the literature is ambiguous, if it is possible to construct the variable using different horizons (i.e., 3-year return versus 4-year return), or if it is possible to update the variable to reflect current market information.

For example, Fama and French (1993) calculate book-to-market ratios once a year in June of year *t* and use those values of book-to-market ratios until May of year *t+1*; however, a firm's market value of equity can change between June of years *t* and *t+1*. So,

[3] Jeffrey Wurgler's website is http://people.stern.nyu.edu/jwurgler/. The St. Louis Federal Reserve's web address is http://research.stlouisfed.org/fred2/series/UMCSENT/. Kenneth French's url is http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html .

in this case I could calculate book-to-market ratios once a year or more frequently. The first 16 financial variables that I consider come from Stambaugh, Yu, and Yuan (2012). These variables are: Campbell et al. (2008) distress risk, Ohlson (1980) O-score, Daniel and Titman (2006) composite equity issuances, net stock issues, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, investment-to-assets, a combination strategy that invests equally in the prior 11 strategies, market beta, firm size, book-to-market, and liquidity beta.

Baker and Wurgler (2006) investigate investor sentiment and firm characteristics that they view as proxies for whether a security is hard-to-value. They believe that hard-to-arbitrage stocks are also hard-to-value. I use 8 financial variables from Baker and Wurgler (2006): firm age; dividends-to-book equity; earnings-to-book equity; external finance; property, plant and equipment-to-assets; research and development-to-assets; return variance; and sales growth. Unlike Baker and Wurgler (2006), who calculate return variance using monthly returns, I calculate return variance using daily returns, following Campbell, Hilscher, and Szilagyi (2008).

The remaining financial variables I consider are analyst coverage, cash flow-to-market equity, credit rating, dividends-to-price, earnings-to-market equity, forecast dispersion, idiosyncratic risk, illiquidity, intermediate momentum, long-term reversal, profit margin, profitability-to-book, return on equity, sales-to-market equity, share turnover, short-run momentum, short-term reversal, standardized unexpected earnings, and unexpected earnings calculated using analysts' forecasts. None of these variables were used in Stambaugh, Yu, and Yuan (2012) or Baker and Wurgler (2006).

These variables were chosen because they seem to have an effect on stock market returns.[4] A more detailed description of each financial variable and trading strategy is given in Appendix A.

1.2.3 Baker and Wurgler (2006) Investor Sentiment Index

Baker and Wurgler (2006) construct their investor sentiment index using 6 proxies for investor sentiment: closed-end fund discount, NYSE share turnover, number and average first-day returns on IPOs, the equity share in new issues, and the dividend premium. They write:

> The closed-end fund discount, CEFD, is the average difference between the net asset values (NAV) of closed-end stock fund shares and their market prices. NYSE share turnover is based on the ratio of reported share volume to average shares listed from the NYSE Fact Book.... We take the number of IPOs, NIPO, and the average first-day returns, RIPO, from Jay Ritter's website, which updates the sample in Ibbotson, Sindelar, and Ritter (1994)…. The share of equity issues in total equity and debt issues is another measure of financing activity that may capture sentiment. Baker and Wurgler (2000) find that high values of the equity share predict low market returns. The equity share is defined as gross equity issuance divided by gross equity plus gross long-term debt issuance using data from the Federal Reserve Bulletin. Our sixth and last sentiment proxy is the dividend premium, P^{D-ND}, the log difference of the average market-to-book ratios of payers and nonpayers. (1655-1656)

Baker and Wurgler then construct their investor sentiment measure in the following manner:

> We form a composite index that captures the common component in the 6 proxies and incorporates the fact that some variables take longer to reveal the same sentiment.[9] We start by estimating the first principal component of the 6 proxies and their lags. This gives us a first-stage index with 12 loadings, 1 for each of the current and lagged proxies. We then compute the correlation between the first-stage index and the current and lagged values of each of the proxies. Finally, we define SENTIMENT as the first principal component of the correlation matrix of 6

[4] Papers that discuss one or more of these financial variables include Amihud (2002), Ang et al. (2006, 2009), Avramov et al. (2012), Ball and Brown (1968), Basu (1977, 1983), Bernard and Thomas (1989, 1990), Chen et al. (2011), Chordia et al. (2001), Chung, Hung, and Yeh (2012), DeBondt and Thaler (1984), Diether et al. (2002), Fama and French (2008), Haugen and Baker (1996, 2008), Jegadeesh (1990), Lakonishok et al. (1994), Livnat and Mendenhall (2006), Novy-Marx (2012a), and Yu (2008).

variables-each respective proxy's lead or lag, whichever has higher correlation with the first-stage index-rescaling the coefficients so that the index has unit variance. This procedure leads to a parsimonious index

$$SENTIMENT_t = -0.241CEFD_t + 0.242TURN_{t-1} + 0.253NIPO_t + 0.257RIPO_{t-1} + 0.112S_t - 0.283P^{D\text{-}ND}_{t-1} \quad (1)$$

where each of the index components has first been standardized. (1657) For *SENTIMENT*, *CEFD* is the closed end fund discount, *TURN* is share turnover, *NIPO* is the number of IPOs, *RIPO* is the average first-day IPO returns, *S* is the share of equity issues measure, and $P^{D\text{-}ND}$ is the dividend premium.

I also use the orthogonalized investor sentiment index, $SENTIMENT^{\perp}$, constructed by Baker and Wurgler. This index is constructed by first regressing each of the 6 proxies of investor sentiment on growth in industrial production, growth in consumer durables, nondurables and services, and a dummy variable for National Bureau of Economic Research recessions. Baker and Wurgler (2006) define $SENTIMENT^{\perp}$ as the first principal component of these orthogonalized 6 proxies of investor sentiment, and find the following equation:

$$SENTIMENT_t^{\perp} = -0.198CEFD_t^{\perp} + 0.225TURN_{t-1}^{\perp} + 0.234NIPO_t^{\perp} + 0.263RIPO_{t-1}^{\perp} + 0.211S_t^{\perp} - 0.243P^{D\text{-}ND,\perp}_{t-1} \quad (2)$$

The Baker and Wurgler (2006) sentiment data are on a monthly frequency from July 1965-December 2010.

1.2.4 University of Michigan Consumer Confidence Index

Each period, either quarterly or monthly, the University of Michigan surveys a representative sample of American households about their current financial situation and how they feel about the economy in the near and long-term. Consumers are asked around 50 questions that cover 3 areas of consumer sentiment: personal finances, business conditions, and buying conditions. The University of Michigan’s Survey of Consumers has been shown to be an accurate measure of the future prospects of the United States economy. (University of Michigan (2013a, 2013b)) The University of Michigan consumer confidence index is available on a quarterly basis from 1952 through 1977 and monthly from January 1978 onwards. I restrict the dates of this index to be from June 1965 through December 2010.

Following Stambaugh, Yu, and Yuan (2012) I construct a University of Michigan residual consumer confidence index. I estimate the following regression equation:

$$UMICH_t = \alpha + \beta_1 Growth\_Indpro_t + \beta_2 Growth\_Consdur_t + \beta_3 Growth\_Consnon_t + \beta_4 Growth\_Consserv_t + \beta_5 Growth\_employ_t + \beta_6 Recess_t + \varepsilon_t, \quad (3)$$

where *UMICH* is the value of the University of Michigan consumer confidence survey, *Growth_Indpro* is the growth of industrial production, *Growth_Consdur* is the growth of durable consumption, *Growth_Consnon* is the growth of nondurable consumption, *Growth_Consserv* is the growth of service consumption, *Growth_employ* is the growth of employment, and *Recess* is a dummy variable for National Bureau of Economic Research recessions.[5]

The University of Michigan residual consumer confidence index is the residual from equation (3). There are 2 other measures of investor sentiment that I use in this paper as robustness checks. The first measure of investor sentiment is the residual from the following regression equation:

$$UMICH_t = \alpha + \beta_1 Level\_Indpro_t + \beta_2 Level\_Consdur_t + \beta_3 Level\_Consnon_t$$

[5] The monthly levels of industrial production, durable consumption, nondurable consumption, service consumption, employment, and the recession dummy variable are available on Jeffrey Wurgler's website. I calculate the five growth variables using these data. I find fairly similar results if I use levels instead of growth rates on the right hand side of regression equation (3). The adjusted R^2 from regression equation (3) using growth rates is approximately 0.35, and if I use levels the adjusted R^2 is approximately 0.60.

$$+\beta_4 Level\_Consserv_t + \beta_5 Level\_employ_t + \beta_6 Recess_t + \varepsilon_t \quad (4)$$

where *Level_Indpro* is the level of industrial production, *Level_Consdur* is the level of durable consumption, *Level_Consnon* is the level of nondurable consumption, *Level_Consserv* is the level of service consumption, *Level_employ* is the level of employment, and *Recess* is a dummy variable for National Bureau of Economic Research recessions.

The final measure of investor sentiment is the residual from the following regression equation:

$$UMICH_t = \alpha + \beta_1 CEFD_t + \beta_2 TURN_t + \beta_3 NIPO_t + \beta_4 RIPO_t + \beta_5 S + \beta 6 P^{D\text{-}NDt} + \varepsilon_t \quad (5)$$

where *CEFD* is the closed-end fund discount, *TURN* is share turnover, *NIPO* is the number of IPOs, *RIPO* is the average first-day IPO returns, *S* is the share of equity issues measure, and $P^{D\text{-}ND}$ is the dividend premium. I will refer to the residual from equation (4) as University of Michigan residual consumer confidence using economic level variables and the residual from equation (5) as University of Michigan residual consumer confidence using sentiment variables.

1.2.5 Delisting Returns

Prior literature has shown that delisting returns can affect the magnitude of trading strategy returns (Beaver, McNichols, Price (2007), Shumway (1997), and Shumway and Warther (1999)). I handle delisting returns in the following manner. If a firm delists in the month following a valid nondelisting return month then I use both the nondelisting return and the delisting return as given. If a firm has a nondelisting return and a delisting return in the same month then I combine these 2 returns into 1 return observation using simple compounding. If a firm delists in a month and has a nondelisting return, but is missing the delisting return, I assume that the overall return for this month was -100%. In some instances, a firm delists but doesn't make a delisting payment until a few months following the last valid nondelisting return. In these cases, I assume that the firm makes the delisting payment in the month immediately following the last valid nondelisting return month. I adopt this policy in order to have a continuous series of monthly firm returns. In the rare instances that this delisting payment is missing I assume that the firm experienced a delisting return of -100%.

1.2.6 Portfolio Formation

I form 10 decile portfolios by sorting firms on 1 of the 84 single-variable trading strategies using NYSE breakpoints in June of each year. I use only common equity with share codes 10 or 11 with share prices between $5 and $1000 and exclude financials (SIC Codes 6000-6999) and utilities (SIC codes 4900-4999). Each portfolio is held from July of year *t* until June of year *t+1*. Value-weighted portfolio returns are calculated for each portfolio.[6]

Following Stambaugh, Yu, and Yuan (2012), portfolio returns for the Campbell et al. (2008) financial distress portfolios start at the end of December 1974 and portfolio returns for the O-score or Investment-to-asset portfolios starts at the end of January 1972. I/B/E/S data were not available prior to June 1984 so portfolio returns for trading strategies that use I/B/E/S data start in July 1984. All other strategies have portfolio returns starting in July 1965.

[6] My results are robust to the inclusion of utilities and financials and firms with extreme share prices (less than $5 or greater than $1000), for holding periods of 1 month, using quarterly COMPUSTAT data, and for equally-weighted portfolios.

After calculating portfolio returns for each of the 84 single-variable trading strategies, I calculate portfolio returns for the 2 combination trading strategies. The first combination strategy, from Stambaugh, Yu, and Yuan (2012), invests equally in the portfolios for Campbell et al. (2008) distress risk, Ohlson's O-score as defined in Chen Novy-Marx, and Zhang (2011), net stock issuances, composite equity issues, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investment-to-assets.

The second combination strategy invests equally in each of the 84 trading strategies. I classify the 2 extreme portfolios into long and short leg portfolios as documented in the literature and form a hedge portfolio as the difference between the long leg and short leg portfolio returns. In the few rare cases where the average return of the hedge leg is negative I switch the long leg and the short leg so that the strategy generates a positive return on average.

1.2.7 Stambaugh, Yu, and Yuan Sentiment Variables

Following Stambaugh, Yu, and Yuan (2012) I construct a few sentiment-related variables. For the 6 measures of sentiment I classify a month as having high sentiment if it is greater than the median level of investor sentiment over the entire sample; otherwise, the month is classified as having low sentiment. Using this definition of high and low investor sentiment I construct 2 dummy variables for each sentiment measure. The first dummy variable indicates if the prior month had high investor sentiment and the second dummy variable indicates if the prior month had low investor sentiment.

1.2.8 Stambaugh, Yu, and Yuan Regressions

After calculating value-weighted returns for each strategy I perform a series of regressions of portfolio returns in excess of the Fama and French (1993) risk-free rate on other financial variables. These regressions follow the methodology used in Stambaugh, Yu, and Yuan (2012) and are designed to test whether portfolio returns are different following high and low sentiment periods and whether portfolio returns can be predicted based on prior sentiment levels. I estimate the following regressions for the long, short, and hedge legs of each strategy and for each sentiment measure:

$$R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + \varepsilon_{i,t} \tag{6}$$

$$R_{i,t} = a + a_H d_{H,t} + \varepsilon_{i,t} \tag{7}$$

$$\mathrm{R_{i,t} = a_H d_{H,t} + a_L d_{L,t} + bMKT_t + cSMB_t + dHML_t} + \varepsilon_{i,t} \tag{8}$$

$$\mathrm{R_{i,t} = a + a_H d_{H,t} + bMKT_t + cSMB_t + dHML_t} + \varepsilon_{i,t} \tag{9}$$

$$R_{i,t} = a + bS_{t-1} + \varepsilon_{i,} \tag{10}$$

$$\mathrm{R_{i,t} = a + bS_{t-1} + cMKT_t + dSMB_t + eHML_t} + \varepsilon_{i,t}, \tag{11}$$

where $d_{H,t}$ is a dummy variable indicating if the prior period had high investor sentiment; $d_{L,t}$ is a dummy variable indicating if the prior period had low investor sentiment; *MKT*, *SMB*, and *HML* are the Fama and French (1993) market, size, and book-to-market factors respectively; and S_{t-1} is the lagged value of 1 of the sentiment measures: either 1 of the 2 Baker and Wurgler (2006) sentiment indices or 1 of the 4 sentiment measures constructed using the University of Michigan consumer confidence index.

The first 4 regressions are used to measure the average excess return following high or low investor sentiment and to measure the difference in excess returns between high and low investor sentiment. The first 2 regressions present the average excess returns following each sentiment state while the second 2 regressions adjust these returns for the returns on the 3 Fama and French (1993) factors. The last 2 regressions are used to test whether the long leg, short leg, or hedge portfolio excess returns can be predicted using the lagged value of investor sentiment. All regressions are estimated using White (1980) standard errors.

1.3 Results

1.3.1 Removal of Highly Correlated Strategies

After calculating long, short, and long-short portfolio returns for each of the 86 strategies I remove those strategies that are highly correlated with another strategy already included as test assets. The removal of highly correlated strategies is completed using 2 steps. Starting with a correlation threshold of 0.75, I first remove strategies that have a correlation of 0.75 or above with the original 16 strategies from Stambaugh, Yu, and Yuan (2012). From the remaining new strategies not previously tested in Stambaugh, Yu, and Yuan (2012), I remove those strategies that have a correlation of 0.75 or above with the other new strategies. When a strategy has a high correlation I remove the strategy that has the highest mean absolute correlation with all the other strategies (inclusive of the 16 strategies from Stambaugh, Yu, and Yuan (2012)). I complete the removal of highly correlated strategies in 2 steps with the idea that this methodology will prevent us from removing more strategies than necessary. However, the results are similar if I remove all highly correlated strategies in 1 step. After completing these 2 steps I am left with a total of 43 different trading strategies. This composes the initial list of strategies. Next I repeat these 2 steps for correlation thresholds of 0.76, 0.77, 0.78, 0.79, and 0.80. If a strategy is kept for 1 of these thresholds that was not previously included as a test asset, I add it to the initial list of strategies and use it as a test asset for all correlation thresholds greater than or equal to the current threshold. In this way I am never adding and subtracting the same strategy. With a correlation threshold of 0.80 I am left with a total of 50 strategies. Table 1.1 lists the 50 trading strategies that remain after removing highly correlated trading strategies and Table 1.2 shows the correlation between the long-short portfolio returns for the 50 different trading strategies. Henceforth I will refer to the 16 trading strategies used in Stambaugh, Yu, and Yuan (2012) as the original trading strategies or as the original strategies and all other trading strategies as the new trading strategies or as the new strategies.

1.3.2 Results Using Baker and Wurgler (2006) Orthogonalized Investor Sentiment

First, I estimate regression equations (4) and (5) using each of the 6 measures of investor sentiment for each of the 50 long leg, short leg, and long-short portfolios. Equation (4) estimates the average excess return following high or low investor sentiment and equation (5) estimates the average difference in excess returns following high and low investor sentiment. Following the reasoning in Stambaugh, Yu, and Yuan (2012), if the securities in the long leg are easy-to-short while the securities in the short leg are hard-to-short then the long leg high-low coefficients from regression equation (5) should not be statistically different from 0, the short leg high-low coefficients should be negative and statistically significant, and the long-short (hedge) portfolio high-low sentiment coefficients should be positive and statistically significant. Table 1.3 reports the number and percentage of high-low sentiment coefficients that are statistically significant for each of the 6 different measures of investor sentiment.

In Table 1.3, Panel A reports the results for long leg portfolios, Panel B for short leg portfolios, and Panel C for long-short portfolios. I use two-tailed *t*-tests for long leg portfolio coefficients and one-tailed *t*-tests for short leg and long-short portfolios. One-tailed *t*-tests are used to test if there is a positive or negative relation between investor sentiment and portfolio returns while two-tailed *t*-tests are used to test if there is a difference in returns between high and low investor sentiment. I first turn to the results using the Baker and Wurgler (2006) orthogonalized investor sentiment index (BW OIS). Consistent with the theoretical predictions I find only 4 out of 50 long leg high-low sentiment coefficients that pass a one-tailed *t*-test before controlling for the Fama and French (1993) factors. Only 8 out of 50 are statistically significant after controlling for the Fama and French (1993) factors. However, for the short leg and the long-short portfolios I find evidence that is inconsistent with these predictions. First, I find that 12 of the 16 (75.00%) short leg portfolios used in Stambaugh, Yu, and Yuan (2012) pass a one-tailed *t*-test (statistically less than 0). On the other hand, for the 34 short leg portfolios not used in Stambaugh, Yu, and Yuan (2012) a much lower number of these portfolios pass a one-tailed *t*-test. I find that 19 (55.88%) out of 34 short leg portfolios pass a one-tailed *t*-test. Overall, using a one-tailed *t*-test, 62% of the short leg portfolio coefficients are statistically less than 0 before controlling for the Fama and French factors, and 64% of the coefficients are statistically less than 0 after controlling for the Fama and French factors.

Panel C in Table 1.3 reports the number of long-short, high-low sentiment coefficients that are statistically significant using a one-tailed *t*-test. Here I find that within the 34 new strategies not used by Stambaugh, Yu, and Yuan (2012), a much smaller percentage of the coefficients pass either a one-tailed or two-tailed *t*-test. Looking at the results prior to controlling for the Fama and French factors we see that for the 16 original strategies 50% pass a one-tailed *t*-test, but for the 34 new strategies only 8.82% pass a one-tailed *t*-test. Overall, only 11 out of 50 (22%) coefficients pass a one-tailed *t*-test. This result is slightly stronger once I control for the Fama and French (1993) factors. Thus, there are a number of profitable strategies where I cannot accept the alternative hypothesis that these strategies are profitable because they are hard-to-short.

I also test whether investor sentiment can predict the returns to the 50 long leg, short leg, and long-short portfolios. If the hard-to-short hypothesis is true, I should not be able to predict the returns to the long leg portfolios, but I should be able to predict the short leg and long-short portfolio returns. For each of the 50 strategies, I estimate equation (8), which regresses portfolio returns in excess of the risk-free rate on lagged investor sentiment, and equation (9), which regresses portfolio excess returns on lagged investor sentiment and the contemporaneous Fama and French (1993) factors. I summarize the number and percentage of statistically significant sentiment coefficients for equations (8) and (9) in Table 1.4. In Table 1.4, the results for the long leg, short leg, and long-short portfolios are presented in Panels A, B, and C, respectively.

From Table 1.4 we can see that most of the long leg coefficients do not pass a one-tailed *t*-test, indicating that there is not a positive predictive relation between investor sentiment and portfolio returns. Before controlling for the Fama and French (1993) factors, I find that 20 out of 50 long leg strategies are statistically significant. I find only 10 out of 50 long leg strategies are still statistically significant after controlling for the Fama and French (1993) factors. This evidence indicates that the long leg portfolios do not invest in hard-to-short securities.

For the 16 short leg portfolios used in Stambaugh, Yu, and Yuan (2012), 13 out of

16 of the investor sentiment coefficients are statistically significant. Additionally, for the 34 new short leg portfolios, 24 out of 34 pass a one–tailed *t*-test testing for a predictive relation between investor sentiment and lagged returns. However, after controlling for the returns on the Fama and French (1993) factors, a smaller number of short leg investor sentiment coefficients are statistically significant; 18 out of 34 new short leg portfolios pass a one-tailed *t*-test testing for a negative relation between investor sentiment and short leg portfolio returns. Overall, investor sentiment exhibits a predictive relation with the returns of 30 out of 50 short leg portfolios. This indicates that there a number of short leg portfolios whose returns are not due to short sale constraints.

I find a much smaller fraction of long-short portfolio returns that can be predicted by investor sentiment. After regressing excess long-short portfolio returns on lagged investor sentiment, only 56.25% of the 16 original strategies are statistically positive and only 23.53% of the 34 new strategies are statistically positive. Overall, of the 50 trading strategies, only 34% of returns to the 50 trading strategies can be predicted using lagged investor sentiment. There is even less evidence that long-short portfolio returns can be predicted by investor sentiment after controlling for the Fama and French (1993) factors. Overall, I find 12 (24%) of the 50 long-short portfolios have a statistically positive relation with investor sentiment.

The evidence found using Baker and Wurgler (2006) orthogonalized investor sentiment indicates that the relation between investor sentiment and profitable trading strategies is much weaker than was previously documented in the literature. Likewise, this evidence seems to indicate that these strategies might be profitable for reasons other than being hard-to-short.

1.3.3 Results Using University of Michigan Residual Consumer Confidence

Next I test whether the results found using the Baker and Wurgler (2006) orthogonalized investor sentiment index (orthogonalized investor sentiment) can also be found using University of Michigan residual consumer confidence constructed using economic growth variables (henceforth, I will call this measure "residual consumer confidence"). I repeat regressions (4)–(9) using residual consumer confidence instead of the Baker and Wurgler (2006) orthogonalized investor sentiment. The results of these regressions are summarized in Tables 1.3 and 1.4.

When using residual consumer confidence instead of orthogonalized investor sentiment, far fewer of the short leg high-low coefficients are statistically significant and have the predicted sign. As shown in Panel B of Table 1.3, before controlling for the Fama and French (1993) factors, only 10% are statistically significant and have the predicted sign, compared to 62% of orthogonalized investor sentiment. After controlling for these factors, the percentage of statistically significant short leg high-low coefficients is again lower using residual consumer confidence than using orthogonalized investor sentiment, 34.00% compared to 64.00%. For long-short portfolio returns, I still find a low percentage that are statistically significant: 24.00% of the 50 trading strategies are statistically positive without controlling for the Fama and French factors and 16.00% are statistically significant afterwards.

Turning to the predictive regression results found using residual consumer confidence (Table 1.4), Panel A shows slightly lower percentages of statistically significant long leg coefficients, 30.00% before and 10.00% after controlling for the Fama and French factors, compared to 40.00% and 20.00% found using orthogonalized investor sentiment.

Panel B of Table 1.4 shows that controlling for the Fama and French factors impacts the number of statistically significant short leg coefficients as well, with 82.35% of new trading strategies being statistically significant prior to controlling for the Fama and French factors and just, 32.35% being statistically significant after. Additionally, the overall percentage of statistically significant coefficients drops from 84.00% to 48.00% after controlling for the 3 Fama and French factors. The drop for the original trading strategies is much smaller, from 87.50% to 81.25%.

Moving to the long-short portfolios in Table 1.4, Panel C, I once again find the pattern of a much lower percentage of statistically significant coefficients for the new trading strategies than for the original 16 trading strategies. Without controlling for the Fama and French factors, 68.75% of the original long-short strategies are statistically significant but only 23.53% of the new long-short strategies are statistically significant. A similar magnitude result is found after controlling for the Fama and French factors.

Overall, the results found using residual consumer confidence provide supporting evidence that the results reported in Stambaugh, Yu, and Yuan (2012) are specific to those particular trading strategies and they do not seem to hold for very many of the new strategies considered in this paper.

1.3.4 Results Using Other Sentiment Measures

As additional robustness checks, I re-run the prior tests using the Baker and Wurgler (2006) raw investor sentiment index, University of Michigan raw consumer confidence index, and the 2 other residual consumer confidence indices constructed using economic level variables and sentiment variables. The results from these tests are reported in Tables 1.3 and 1.4. I once again find that the percentage of statistically significant coefficients drops when I move from the 16 original trading strategies to the 34 new trading strategies. Sometimes the percentage of statistically significant coefficients is high for a particular sentiment measure without controlling for the Fama and French factors; however, this percentage drops once I control for the Fama and French factors. Again, I find that the percentage of statistically significant short leg and long-short coefficients with the predicted sign is lower using all 50 trading strategies than when using the 16 original trading strategies.

1.3.5 Results for Different Correlation Thresholds

To address a concern that the results may be specific to the correlation threshold of 0.80, I repeat the prior tests for correlation thresholds between 0.75 and 1.00 using 0.01 increments. At a correlation threshold of 1.00, I am not excluding any of the 86 trading strategies, even if 1 of those strategies is perfectly correlated with another strategy already included as a test asset. In Table 1.5, I document when a particular variable is added to the list of test assets after increasing the correlation cutoff threshold from 0.75 to 0.99 in increments of 0.01. Seven strategies are perfectly correlated with another strategy already under consideration. These strategies are listed in Table 1.6.

I previously used 4 different tests to investigate whether the hard-to-short hypothesis explains the returns to profitable trading strategies. First, I looked at average excess return differences following high and low investor sentiment periods with and without controlling for the returns on the Fama and French (1993) factors. Then, I investigated whether the returns to long, short, and long-short portfolios can be predicted using lagged investor sentiment with and without controlling for the Fama and French (1993) factors. I conducted these 4 tests using 6 different measures of investor sentiment:

Baker and Wurgler (2006) orthogonalized investor sentiment; Baker and Wurgler (2006) raw investor sentiment; University of Michigan residual consumer confidence constructed using economic growth, economic level, and sentiment input variables; and University of Michigan raw consumer confidence. I repeat these 4 tests for the long-short portfolios and for all correlation thresholds between 0.75 and 1.00, increasing the correlation threshold by 0.01 after each series of tests, and plot the acceptance rate from each test in Figures 1.1 and 1.2. For brevity, I only report the results using Baker and Wurgler (2006) orthogonalized investor sentiment and University of Michigan residual consumer confidence. Similar results are obtained using the 4 other measures of investor sentiment. I define the acceptance rate as the number of coefficients that are statistically significant using a 1 tailed *t*-test, H_0: $\mu \leq 0$, divided by the total number of coefficients.

In each figure, Panels A and B, respectively, plot the acceptance rates for the coefficients, testing whether the difference in average excess returns following high and low investor sentiment is statistically significant with and without controlling for the Fama and French (1993) factors, respectively. Panels C and D plot the acceptance rate for the coefficients, testing whether the lagged investor sentiment coefficient is statistically significant in a predictive regression of long-short excess returns with and without controlling for the Fama and French (1993) factors, respectively. Figure 1.1 reports the results using Baker and Wurgler (2006) orthogonalized investor sentiment and Figure 1.2 reports the results using University of Michigan residual consumer confidence. Each panel plots the acceptance rates for the original 16 trading strategies, the new strategies that are less than the correlation threshold, and all strategies that are less than the correlation threshold. The acceptance rate for the 16 original strategies does not change for different correlation thresholds because these strategies are always included in the 4 tests.

These plots show that the acceptance rates for the new strategies is always below the acceptance rate for the 16 original strategies, and most of the time there is a fairly large difference between the acceptance rate for the 16 original strategies and the new strategies considered in this paper. Sometimes the acceptance rates increase or decrease as the correlation threshold increases to 1.00. Generally, this occurs because, as the correlation threshold increases, I am adding strategies that are highly correlated with strategies that previously rejected or failed to reject the null hypothesis. Ideally, if the hard-to-short hypothesis holds, we would see an acceptance rate of 1.00 for all strategies. However, these plots show an overall acceptance rate that is usually below 0.40. Therefore, there is only weak support for the hard-to-short hypothesis. Furthermore, the main result, that these strategies are profitable for reasons other than short sale limits to arbitrage, is not extremely sensitive to the inclusion or exclusion of highly correlated strategies.

1.3.6 Investor Sentiment and Economic Conditions Results

So far, the evidence indicates that there is a strong relation between investor sentiment and the 16 original trading strategies but a weak relation between investor sentiment and the 34 additional trading strategies. Recent work by Sibley et al. (2014) suggests that the Baker and Wurgler (2006) investor sentiment index is related to macroeconomic conditions. Thus, it could be the case that the original trading strategies invest in securities that are sensitive to macroeconomic conditions while the 34 additional strategies invest in securities that are not sensitive to macroeconomic conditions. To test this explanation, I estimate the conditional CAPM model that was used in Petkova and Zhang (2005) and Cooper et al. (2008). I estimate the following conditional CAPM models:

$$R_{t+1} = a + a_H d_{H,t} + (b_0 + b_1 Div_t + b_2 DEF_t + b_3 TERM_t + b_4 TB_t) r_{m,t+1} + \varepsilon_{t+1} \quad (12)$$

and

$$R_{t+1} = a + b\, S_t + (c_0 + c_1 Div_t + c_2 DEF_t + c_3 TERM_t + c_4 TB_t) r_{m,t+1} + \varepsilon_{t+1}\ , \quad (13)$$

where $d_{H,t}$ is a dummy variable indicating if the prior period had high investor sentiment, Div is the 12-month dividend yield on the value-weighted market portfolio, DEF is the default spread, TERM is the term spread, TB is 3-month Treasury bill rate, and r_m is the excess return on the value-weighted market portfolio. The dividend yield is calculated following Fama and French (1988). I estimate regressions 1 and 2 for each of the 50 trading strategies and report the percentage of statistically significant coefficients in Table 1.7. If the returns to the original strategies are driven by macroeconomic conditions while the new strategies are not, then there should be a large decrease in the percentage of significant coefficients using the conditional CAPM model. However, the results presented in Table 1.7 do not support this explanation. Compared to the percentage of significant coefficients without controlling for the macroeconomic factors, there is very little change in the percentage of significant coefficients using the conditional CAPM model. Additionally, similar results are obtained whether I estimate the difference in returns between high and low sentiment states or I regress returns on lagged investor sentiment. These results suggest that the reason I find a strong relation between investor sentiment and 1 group of strategies and a weak relation using another group of strategies is not due to 1 group taking positions in securities sensitive to macroeconomic conditions.

To further assess whether the results between investor sentiment and profitable trading is due to macroeconomic conditions, I construct the predicted and residual investor sentiment measures used in Sibley et al. (2013). For each of the 6 sentiment measures, I construct predicted and residual investor sentiment by regressing each measure on 13 financial variables. The 13 financial variables are the U.S. unemployment rate, growth rate in inflation, growth rate in consumption, growth rate in disposable personal income, growth rate in industrial production, NBER recession indicator variable, 3-month Treasury bill rate, default spread, term spread, dividend yield, value-weighted market return, stock market volatility, and a liquidity risk factor. The fitted value from these regressions is defined as predicted investor sentiment while the residual is defined as residual investor sentiment.

Based on the arguments presented in Sibley et al. (2013), if the relation between investor sentiment and profitable trading strategies is due to investor sentiment acting as a proxy for the state of the economy then there should be a strong relation between predicted investor sentiment and the returns to the trading strategies, but a weak relation between residual investor sentiment and the returns to the trading strategies. Table 1.8 shows the percentage of statistically significant investor sentiment coefficients using predicted and residual investor sentiment in place of the 6 raw sentiment measures, with Panel A showing the results for high-low investor sentiment coefficients and Panel B showing the results for predictive regression coefficients.

Turning to the high-low investor sentiment results, without controlling for the Fama and French (1993) factors, we can see that there is strong relation between predicted investor sentiment and the short leg portfolios. This result is obtained for 4 of the 6 investor sentiment measures and is consistently found for both the original and the new strategies. On the other hand, now I am also finding a statistically significant relation between investor sentiment and a nontrivial portion of the long leg portfolios. This result is inconsistent with the prediction of no relation between investor sentiment and long leg portfolio returns.

While the portion of investor sentiment that is related to the macro economy explains the short leg portfolios, it does not seem to do a better job of explaining the hedge portfolio returns than the raw investor sentiment measures. Furthermore, I again find a stronger relation between investor sentiment and the original long-short portfolios than between investor sentiment and the new long-short portfolios. However, the macroeconomic component of investor sentiment does not seem to produce a stronger relation than when using the raw investor sentiment measures. Fairly similar results are found after controlling for the Fama and French (1933) factors, except now the percentage of significant coefficients has a larger drop between the original and new strategy groups.

If the Sibley et al. (2013) hypothesis that investor sentiment proxies for macroeconomic conditions is correct, there should be a weak relation between the residual investor sentiment measures and profitable trading strategies. Looking at the results for the long leg and short leg portfolios, for the most part, I find evidence consistent with this explanation. However, even when I use the component of investor sentiment that is unrelated to the macro economy, I still find a relation between investor sentiment and a portion of the long-short portfolios. This suggests that unlike in Sibley et al. (2013), there is a relation between investor sentiment and some trading strategies, although the majority of the strategies do not have a relation with investor sentiment. Additionally, once I control for the Fama and French (1993) factors, there is a portion of the short leg portfolios that have a relation with residual investor sentiment. Thus, macroeconomic conditions are not able to fully explain the relation between investor sentiment and some profitable trading strategies.

Moving to the predictive regression coefficients presented in Panel B, prior to controlling for the Fama and French (1993) factors, I again find a strong relation between predicted investor sentiment and the short leg portfolios. However, there is a relation between predicted investor sentiment and some of the long leg portfolios. The relation between predicted investor sentiment and long-short portfolios is much stronger for the original strategies than for the additional strategies. This result is obtained with or without controlling for the Fama and French (1933) factors.

Once more, prior to controlling for the Fama and French (1993) factors, there is a weak relation between residual investor sentiment and the long leg and short leg portfolios. However, even when I use residual investor sentiment, I still find a relation between the original long-short strategies and investor sentiment. This implies that the relation between investor sentiment and the original trading strategies is not due to those strategies investing in securities sensitive to macroeconomic conditions. Further, once I control for the Fama and French (1993) factors, the relation between investor sentiment and short leg portfolios reappears in some instances.

Overall, these results suggest that while macroeconomic conditions may explain the relation between investor sentiment and short leg portfolio returns, but macroeconomic conditions are not able to explain the relation between investor sentiment and the long-short trading strategies.

1.3.7 Huang et al. (2015) Aligned Investor Sentiment Results

Up to this point, it does not seem that differences in sensitivity to macroeconomic conditions can explain why there is a strong relation between investor sentiment and the original strategies but a weak relation between investor sentiment and the additional strategies. In a recent paper Huang et al. (2015) propose that the Baker and Wurgler (2006) sentiment measures contain noise. They suggest a new measure of investor sentiment that uses partial least squares (PLS) to remove noise from the Baker and Wurgler (2006) investor sentiment measure. They find that their measure of investor sentiment has greater predictive power than the Baker and Wurgler (2006) investor sentiment measure.

I assess whether the results reported so far are robust to the use of the Huang et al. (2015) aligned investor sentiment measure. Goufu Zhou kindly provides the Huang et al. (2015) aligned investor sentiment measure on his personal website. I also construct 2 other measures of investor sentiment: predicted and residual Huang et al. (2015) aligned investor sentiment. These 2 measures are the fitted values and residual values from regressing the raw Huang et al. (2015) aligned investor sentiment measure on the 13 Sibley et al. (2013) financial variables. In Table 1.9, I present the percentage of statistically significant investor sentiment coefficients for these 3 investor sentiment measures. First, looking at the percentage of statistically significant high-low coefficients, there is now a new result. Before, an extremely small percentage of the long leg portfolios had a relation with investor sentiment, but now a large percentage of the long leg portfolios has a relation with investor sentiment. This result is found using either the raw or predicted Huang et al. (2015) aligned investor sentiment measures, but disappears using the residual measure. Interestingly, this result is found both for the original strategies as well as for the new strategies.

Turning to the short leg coefficients, almost all of the 50 short leg portfolios have a relation with investor sentiment. This relation diminishes using the residual sentiment measure, but still at least 50% of the short leg portfolios has a relation with investor sentiment. These results suggest that investor sentiment has an effect on both the long leg and the short leg portfolios.

Consistent with the results found using the Baker and Wurgler (2006) and University sentiment measures, I find a strong relation between investor sentiment and the original long-short portfolios, but a much weaker relation between investor sentiment and the new long-short portfolios. This result is strongest using the raw or the predicted Huang et al. (2015) aligned investor sentiment measures. A weaker relation is obtained using the residual Huang et al. (2015) aligned investor sentiment measure, although 38% of the 50 trading strategies still has a relation with investor sentiment.

While the prior results suggest that there is a strong relation between investor sentiment and the long leg and short leg portfolios, a different result is obtained after controlling for risk. After controlling for the returns on the Fama and French (1993) factors, a tiny portion of the 50 trading strategies still have a relation with investor sentiment. Overall, 6% of the 50 long leg portfolios have a relation with the raw and residual investor sentiment measures and 12% have a relation with the predicted investor sentiment measure. Further, the relation between investor sentiment and short leg portfolio returns is much weaker after controlling for the Fama and French (1993) factors. The percentage of significant coefficients is 46%, 52%, and 0% using the raw, predicted, and residual sentiment measures, respectively. Additionally, the long-short portfolios exhibit a weaker relation with the Huang et al. (2015) investor sentiment measures. Typically, less than 20% of the 50 strategies have a statistically significant relation with investor sentiment.

The percentage of statistically significant predictive regression coefficients are presented in Panel B. of Table 1.9. Similar to the results for the high-low investor sentiment coefficients, prior to controlling for risk, there is a strong predictive relation between the long leg and short leg portfolios, but a much weaker relation after controlling for risk. Further, the relation between investor sentiment and the long-short portfolios is strong for the 16 original strategies, but much weaker for the 34 additional strategies.

In totality, the prior results confirm the results found using the Baker and Wurgler (2006) and the University of Michigan sentiment measures. There is a strong relation between the 16 original strategies but a much weaker relation between the 34 additional strategies and investor sentiment. The question that still needs to be answered is which group of strategies is representative of the population. Is it the case that there is strong relation between investor sentiment and cross-sectional anomalies and the additional strategies are not representative of the population or is it the case that there is a weak relation between investor sentiment and the 16 original strategies are not representative of the population? In the next section, I try to answer this question using simulated long, short, and long-short portfolios.

1.3.8 Simulation Results

To further assess whether investor sentiment affects the returns to cross-sectional anomalies, I construct simulated long, short, and long-short portfolios. Each June, I randomly assigned each stock to 1 of 10 decile portfolios. Value-weighted returns are then calculated for each portfolio from July of year *t* until June of year *t+1*. I then define the long leg as the decile with the highest average return and the short leg as the decile with the lowest average return. The long-short portfolio is then constructed using the long leg and short leg portfolios. Then, I estimate the high-low investor sentiment and the predictive regression coefficients for the long, short, and long-short portfolios using each of the raw, predicted, and residual sentiment measures. This procedure is repeated 10,000 times. The percentage of statistically significant coefficients across all 10,000 trading strategies is presented in Table 1.9, with Panel A presenting the results for high-low investor sentiment coefficients and Panel B presenting the results for predictive regression coefficients.

The results using the raw Baker and Wurgler (2006) and University of Michigan sentiment measures are consistent with the results presented for the new trading strategies, that there is a weak relation between profitable trading strategies and investor sentiment. Based on the evidence presented in Panel A.1 of Table 1.9, there is a weak relation between the long leg and investor sentiment. For the most part there is a weak relation between short leg portfolios and investor sentiment and a weak relation between investor sentiment and long-short portfolios. Typically, less than 10% of the long-short portfolios exhibit a relation with investor sentiment.

A different result is obtained using the raw Huang et al. (2015) aligned investor sentiment measure (AIS). Using this measure there is strong relation between investor sentiment and the long leg and short leg portfolios but a very weak relation between investor sentiment and the long-short portfolios. Out of the 10,000 portfolios, over 80% of the long leg portfolios and over 99% of the short leg portfolios have a relation with investor sentiment, but less than 11% of the long-short portfolios have a relation with investor sentiment.

Prior to controlling for the Fama and French (1993) factors, there is a weak relation between 5 of the 6 predicted sentiment measures and the long leg portfolios and a stronger relation between investor sentiment and the short leg portfolios. Using the University of Michigan residual sentiment constructed using GDP growth variables, more than 97% of the short leg portfolios have a relation with investor sentiment. While the short leg has a relation with investor sentiment, overall each long-short trading strategy has a weak relation with investor sentiment; less than 10% of the strategies have a statistical relation with investor sentiment.

After controlling for the Fama and French (1993) factors, there is a weak relation between predicted investor sentiment and the long leg, short leg, and long-short portfolios. Further, although the overall relation is weak, there are still around 10% of the strategies with a relation between the component of sentiment related to the economy and trading strategy returns. This result is found even when using the Huang et al. (2015) aligned investor sentiment measure.

The results change using residual sentiment. There is now a weak relation between the short leg portfolios and investor sentiment. The long leg portfolios exhibit a relation with investor sentiment using 2 of the sentiment measures, but this result diminishes significantly after controlling for the Fama and French (1993) factors. Interestingly, there is still a relation between investor sentiment and a subsample of the long-short portfolios. This evidence is inconsistent with the macroeconomic hypothesis since the percentage of significant coefficients does not drop to 0 after removing the component of sentiment related to the economy.

Finally, Panel B of Table 1.9 shows the simulation results from the predictive regressions. By and large, the results are fairly similar to the results from the high-low sentiment regressions. Before controlling for the Fama and French (1993) factors, the long leg has a weak relation with 5 of the 7 sentiment measures. The long leg portfolios have a strong relation with University of Michigan residual investor sentiment constructed using the 6 Baker and Wurgler (2006) sentiment variables and a strong relation with the Huang et al. (2015) aligned investor sentiment. The short leg has a stronger relation with investor sentiment, especially with University of Michigan residual investor sentiment constructed using the 6 Baker and Wurgler (2006) sentiment variables and with the Huang et al. (2015) aligned investor sentiment. Using the Huang et al. (2015) measure, 100% of the short leg coefficients are statistically significant. The overall relation between the long-short trading strategies is weak. Across all 7 measures, I consistently find around 10% of the strategies that have a relation with investor sentiment.

Once I control for risk, the relation between investor sentiment and cross-sectional anomalies changes drastically. After controlling for the Fama and French (1993) factors, typically around 3% of the long leg portfolios have a predictive relation with investor sentiment, around 20% of the short leg portfolios exhibit a predictive relation, and around 10% of the long-short portfolios exhibit a predictive relation. Thus, once I control for risk, there is a weak predictive relation between the long leg, short leg, and long-short portfolios. Similar results are obtained using the component of the sentiment measures that is related to the economy. However, the relation between the short leg portfolios is often strengthened using the predicted investor sentiment measures. Still, once again after controlling for risk, there is a weak relation between investor sentiment and cross-sectional anomalies.

The percentage of significant high-low and predictive regression coefficients is presented in Panels A.3 and B.3 of Table 1.10. The results indicate that there is a weak relation between investor sentiment and the long, short, and long-short portfolios. Interestingly, 98.99% of the long leg high-low coefficients have a statistically significant relation with the portion of Baker and Wurgler (2006) investor sentiment that is unrelated to the 13 Sibley et al. (2013) variables. However, this result changes once I control for risk. After controlling for risk, the percentage of significant long leg portfolios drops from 98.99% to 7.15%. Additionally, I do not find a predictive relation between this measure and the long leg portfolios. Another interesting finding is that residual Huang et al. (2015) aligned investor sentiment still has predictive power before controlling for risk, but after controlling for risk this measure has very little predictive power. Additionally, the component of sentiment that is unrelated to the economy still has predictive power. Therefore, macroeconomic risk is not able to fully explain why certain cross-sectional anomalies have a relation with investor sentiment.

Overall, these results confirm that there is a weak relation between trading strategy returns and investor sentiment and that macroeconomic conditions are not able to fully explain the relation between a small subsample of profitable trading strategies and investor sentiment. Thus, while the 16 original strategies have a relation with investor sentiment, the overwhelming majority of strategies have a weak relation with investor sentiment. Thus, it appears that the 34 additional strategies are more representative of the population of profitable long-short strategies. From these results, it seems reasonable to conclude that there is a weak relation between investor sentiment and cross-sectional anomalies.

1.4 Conclusion

Using a large sample of profitable trading strategies, I test the hypothesis that these strategies are profitable because they invest in hard-to-short securities. Prior literature, such as Stambaugh, Yu, and Yuan (2012), has argued that the firms in the long leg of each trading strategy should not be hard-to-short, and therefore, there should be no difference in returns following high or low investor sentiment and there should be no predictive relation between lagged investor sentiment and long leg returns. I find evidence consistent with this portion of the hard-to-short hypothesis. In addition, the short leg returns of each trading strategy should exhibit a negative relation with lagged investor sentiment and the returns following high investor sentiment should be lower than those returns following low investor sentiment. These hypotheses follow from the premise that the securities in the short leg are hard-to-short. Compared to the prior literature, I find weaker support for the hypothesis that the securities in the short leg portfolio of each strategy are hard-to-short. Finally, for the long-short portfolio, the returns following high sentiment should be larger than the returns following low sentiment, and there should be a positive relation between lagged investor sentiment and future returns. I test these 2 claims but find less evidence in favor of these claims than was previously reported in the literature. These results indicate that the returns to a large number of trading strategies are not due to short sale constraints. Thus, the higher returns earned to certain trading strategies could be due to risk rather than mispricing. Overall, these results indicate that it is important to use a representative sample when testing financial theory. If the sample is not representative of the population then the inferences made may be different from what actually exists in nature.

Table 1.1

Trading strategies remaining that have correlations less than 0.80. This table lists the 50 trading strategies that remain after removing strategies that are highly correlated with other trading strategies. Initially I have a total of 86 different trading strategies. I then remove strategies that have a correlation of 0.75 or above with the 16 trading strategies previously tested in the literature (i.e., Stambaugh, Yu, and Yuan (2012)). Henceforth, I will refer to these 16 strategies as the original strategies and all other strategies as new strategies. Next, of the remaining new strategies, I remove those strategies that have a correlation of 0.75 with another member of the new strategies. When a strategy has a correlation of 0.75 or above with another strategy I remove the strategy with the highest mean absolute correlation with the new strategies. This composes the initial list of 42 test strategies. Next I increase the correlation cutoff threshold from 0.75 to 0.80 in increments of 0.01 and repeat the removal of highly correlated strategies. As I do this, if a strategy that was previously removed is no longer removed then I add this strategy to the initial 42 strategies list. Thus, the strategies used in each test are updated each iteration and I never add and remove the same strategy.

	Variable Name		Variable Name
(1)	Campbell Distress	(35)	Forecast Dispersion
(2)	O-Score (1)	(42)	Intermediate Momentum
(3)	Net Stock Issues	(43)	Investments to Assets (2)
(4)	Daniel Titman Composite	(44)	Investments to Assets (3)
(5)	Accruals (1)	(45)	Investments to Assets (4)
(6)	Net Operating Assets	(46)	Investments to Assets (5)
(7)	Momentum (1)	(47)	Liquidity Beta (2)
(8)	Gross Profitability	(48)	Liquidity Beta (3)
(9)	Asset Growth (1)	(49)	Long-term Reversal (1)
(10)	Return on Assets (1)	(50)	Long-term Reversal (2)
(11)	Investments to Assets (1)	(51)	Long-term Reversal (3)
(12)	Combination Strategy (1)	(52)	Market Beta (2)
(13)	Market Beta (1)	(54)	Momentum (2)
(14)	Firm Size	(59)	Profit Margin
(15)	Book-to-market (1)	(60)	PPE-to-Assets
(16)	Liquidity Beta (1)	(61)	R&D-to-Assets
(17)	Accruals (2)	(73)	Return Variance (8)
(18)	Age	(74)	Sales Growth (1)
(19)	Analyst Coverage	(75)	Sales Growth (2)
(24)	Cash flow-to-market equity (2)	(77)	Sales-to-market equity (1)
(27)	Dividends-to-price (1)	(80)	Short-run momentum (1)
(31)	Earnings-to-market equity (2)	(81)	Short-run momentum (2)
(32)	Earnings-to-market equity (3)	(82)	Short-term Reversal
(33)	External Finance (1)	(83)	SUE
(34)	External Finance (2)	(84)	Unexpected Earnings (1)

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Table 1.2

Correlation between 50 strategies after removing highly correlated strategies. This table shows the correlation between long-short portfolio returns for the 50 strategies that remain after removing strategies with a correlation of at least 0.80 with another remaining strategy.

Panel A. Correlations between 16 original long-short strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(1) Campbell Distress	1															
(2) O-Score (1)	0.71	1														
(3) Net Stock Issues	0.41	0.61	1													
(4) Daniel Titman Composite	0.30	0.46	0.71	1												
(5) Accruals (1)	-0.04	0.14	0.35	0.36	1											
(6) Net Operating Assets	0.26	0.39	0.37	0.24	0.16	1										
(7) Momentum (1)	0.49	0.18	0.00	0.02	0.02	0.00	1									
(8) Gross Profitability	0.48	0.56	0.34	0.17	0.02	0.33	0.10	1								
(9) Asset Growth (1)	0.01	0.11	0.56	0.56	0.45	0.23	-0.08	-0.02	1							
(10) Return on Assets (1)	0.67	0.76	0.40	0.22	-0.09	0.26	0.16	0.65	-0.13	1						
(11) Investments to Assets (1)	-0.01	0.04	0.26	0.16	-0.08	0.22	-0.16	0.20	0.29	0.05	1					
(12) Combination Strategy (1)	0.76	0.82	0.77	0.66	0.39	0.52	0.35	0.59	0.45	0.67	0.24	1				
(13) Market Beta (1)	0.53	0.61	0.66	0.68	0.35	0.18	0.11	0.35	0.44	0.45	0.05	0.71	1			
(14) Firm Size	-0.55	-0.75	-0.43	-0.31	-0.17	-0.28	-0.20	-0.31	-0.02	-0.54	0.18	-0.55	-0.49	1		
(15) Book-to-market (1)	-0.40	-0.33	0.14	0.32	0.20	-0.13	-0.23	-0.44	0.50	-0.48	0.14	-0.14	0.04	0.37	1	
(16) Liquidity Beta (1)	-0.17	-0.12	-0.06	0.05	-0.01	0.08	-0.10	-0.08	0.02	-0.11	0.00	-0.10	-0.10	0.09	0.13	1

Table 1.2 continued

Panel B. Correlations between 16 original long-short strategies and 34 new long-short strategies

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
(17) Accruals (2)	0.13	0.09	0.17	0.21	0.29	0.19	0.21	-0.08	0.17	-0.06	-0.15	0.21	0.19	-0.12	0.10	-0.09
(18) Age	0.48	0.71	0.77	0.68	0.34	0.29	-0.01	0.31	0.51	0.47	0.11	0.73	0.78	-0.58	0.14	-0.10
(19) Analyst Coverage	0.33	0.68	0.49	0.28	0.21	0.26	0.11	0.36	0.19	0.49	0.10	0.53	0.23	-0.78	-0.17	-0.15
(24) Cash flow-to-market equity (2)	0.07	0.33	0.58	0.56	0.47	0.13	-0.09	0.08	0.53	0.16	0.12	0.45	0.49	-0.21	0.43	0.03
(27) Dividends-to-price (1)	0.25	0.52	0.66	0.72	0.37	0.19	-0.15	0.17	0.49	0.29	0.06	0.55	0.75	-0.47	0.26	0.02
(31) Earnings-to-market equity (2)	0.27	0.43	0.48	0.53	0.12	-0.03	-0.06	0.18	0.32	0.41	0.15	0.44	0.51	-0.28	0.25	-0.02
(32) Earnings-to-market equity (3)	0.35	0.42	0.41	0.44	0.10	0.06	-0.06	0.21	0.19	0.48	0.05	0.41	0.46	-0.30	0.13	0.02
(33) External Finance (1)	0.21	0.32	0.63	0.56	0.46	0.19	0.00	0.17	0.76	0.15	0.33	0.58	0.50	-0.11	0.38	-0.03
(34) External Finance (2)	0.26	0.34	0.46	0.49	0.29	0.03	0.15	0.22	0.46	0.28	0.16	0.49	0.48	-0.16	0.22	0.03
(35) Forecast Dispersion	0.66	0.66	0.60	0.48	-0.01	0.09	0.25	0.63	0.16	0.72	0.25	0.71	0.69	-0.41	-0.21	-0.30
(42) Intermediate Momentum	-0.51	-0.23	0.09	0.09	0.11	0.04	-0.76	-0.12	0.20	-0.22	0.18	-0.25	-0.06	0.24	0.39	0.06
(43) Investments to Assets (2)	0.19	0.17	0.53	0.59	0.30	0.09	0.00	-0.04	0.69	-0.02	0.28	0.43	0.57	-0.03	0.55	-0.02
(44) Investments to Assets (3)	0.02	0.11	0.56	0.63	0.44	0.06	-0.09	-0.07	0.75	-0.16	0.16	0.38	0.52	-0.07	0.51	-0.03
(45) Investments to Assets (4)	0.15	-0.06	-0.13	-0.09	-0.13	0.11	0.23	0.04	-0.06	-0.04	0.18	0.03	-0.16	0.24	-0.10	-0.11
(46) Investments to Assets (5)	-0.07	-0.12	0.15	0.18	0.08	-0.04	-0.10	-0.10	0.32	-0.20	0.23	0.03	0.07	0.21	0.36	0.11
(47) Liquidity Beta (2)	0.00	-0.01	-0.03	-0.01	-0.07	-0.03	-0.09	-0.03	0.01	0.05	-0.01	-0.04	-0.08	0.07	-0.01	0.39
(48) Liquidity Beta (3)	-0.18	-0.19	-0.12	-0.01	-0.04	-0.07	-0.09	-0.12	-0.03	-0.11	0.00	-0.16	-0.13	0.15	0.13	0.75
(49) Long-term Reversal (1)	0.50	0.25	-0.05	0.00	-0.02	-0.01	0.76	0.18	-0.22	0.31	-0.16	0.31	0.11	-0.30	-0.41	-0.16
(50) Long-term Reversal (2)	0.52	0.34	0.04	0.01	-0.08	-0.05	0.64	0.24	-0.26	0.44	-0.15	0.32	0.20	-0.39	-0.46	-0.16
(51) Long-term Reversal (3)	-0.54	-0.39	-0.03	0.01	0.07	0.01	-0.60	-0.27	0.26	-0.49	0.23	-0.32	-0.19	0.42	0.47	0.14
(52) Market Beta (2)	-0.48	-0.56	-0.58	-0.56	-0.28	-0.12	-0.08	-0.38	-0.40	-0.43	-0.09	-0.64	-0.85	0.44	-0.05	0.15
(54) Momentum (2)	0.20	-0.03	-0.06	-0.02	0.10	0.02	0.75	-0.04	-0.05	-0.02	-0.17	0.17	-0.04	-0.04	-0.07	0.00
(59) Profit Margin	0.56	0.73	0.45	0.34	0.21	0.22	0.12	0.38	0.07	0.71	-0.15	0.59	0.52	-0.69	-0.31	-0.09
(60) PPE-to-Assets	0.13	0.15	0.08	0.10	0.07	-0.08	0.03	0.02	0.07	0.06	-0.14	0.09	0.09	-0.23	0.00	0.01
(61) R&D-to-Assets	0.04	0.15	-0.18	-0.28	-0.18	0.38	0.04	0.20	-0.36	0.16	-0.10	-0.01	-0.29	-0.16	-0.50	-0.09
(73) Return Variance (8)	-0.21	-0.40	-0.55	-0.56	-0.29	-0.10	0.24	-0.21	-0.44	-0.25	-0.12	-0.45	-0.69	0.28	-0.25	0.08
(74) Sales Growth (1)	-0.07	0.05	0.46	0.48	0.45	0.12	-0.19	-0.07	0.74	-0.16	0.24	0.30	0.36	-0.04	0.49	0.07
(75) Sales Growth (2)	0.03	0.09	0.46	0.54	0.34	0.03	-0.06	-0.03	0.66	-0.09	0.27	0.35	0.46	0.00	0.46	0.02
(77) Sales-to-market equity (1)	-0.42	-0.34	0.11	0.25	0.08	-0.16	-0.31	-0.34	0.42	-0.45	0.31	-0.18	-0.01	0.46	0.76	0.21
(80) Short-run momentum (1)	0.12	0.15	0.08	0.12	0.11	0.08	0.44	0.13	-0.06	0.18	-0.17	0.23	0.17	-0.18	-0.14	0.03
(81) Short-run momentum (2)	0.14	0.09	0.12	0.12	0.12	0.05	0.45	0.09	0.04	0.13	-0.08	0.24	0.16	-0.06	-0.01	0.06
(82) Short-term Reversal	0.22	0.14	-0.08	0.02	0.01	0.08	0.44	0.07	-0.16	0.11	-0.23	0.15	0.11	-0.20	-0.31	-0.04
(83) SUE	0.54	0.36	0.11	0.02	0.01	0.08	0.38	0.26	-0.08	0.39	0.00	0.32	0.17	-0.22	-0.33	-0.21
(84) Unexpected Earnings (1)	0.02	0.05	0.07	0.08	0.01	0.11	0.09	0.04	0.01	0.02	0.09	0.08	0.01	-0.04	-0.02	0.22

Table 1.2 continued

Panel C. Correlations between 28 new long-short strategies

	(17)	(18)	(19)	(24)	(27)	(31)	(32)	(33)	(34)	(35)	(42)	(43)	(44)	(45)	(46)	(47)	(48)	(49)	(50)	(51)	(52)	(54)	(59)	(60)	(61)	(73)	(74)	(75)	(77)	(80)	(81)	(82)	(83)	(84)
(17) Accruals (2)	1																																	
(18) Age	0.15	1																																
(19) Analyst Coverage	0.08	0.55	1																															
(24) Cash flow-to-market equity (2)	0.21	0.58	0.37	1																														
(27) Dividends-to-price (1)	0.14	0.75	0.38	0.57	1																													
(31) Earnings-to-market equity (2)	0.00	0.60	0.33	0.53	0.58	1																												
(32) Earnings-to-market equity (3)	0.01	0.52	0.26	0.40	0.51	0.78	1																											
(33) External Finance (1)	0.14	0.62	0.37	0.63	0.50	0.48	0.39	1																										
(34) External Finance (2)	0.11	0.47	0.28	0.40	0.39	0.38	0.34	0.55	1																									
(35) Forecast Dispersion	0.02	0.59	0.29	0.30	0.46	0.43	0.45	0.40	0.44	1																								
(42) Intermediate Momentum	-0.13	0.07	-0.04	0.22	0.17	0.05	0.06	0.16	-0.05	-0.21	1																							
(43) Investments to Assets (2)	0.19	0.60	0.10	0.55	0.54	0.50	0.38	0.69	0.52	0.32	0.11	1																						
(44) Investments to Assets (3)	0.18	0.55	0.15	0.54	0.57	0.36	0.21	0.63	0.42	0.21	0.21	0.71	1																					
(45) Investments to Assets (4)	0.01	-0.22	-0.17	-0.18	-0.31	-0.16	-0.18	-0.08	-0.12	0.07	-0.22	-0.02	-0.12	1																				
(46) Investments to Assets (5)	0.02	0.09	-0.04	0.15	0.02	0.02	-0.08	0.24	0.19	0.04	0.17	0.27	0.34	-0.01	1																			
(47) Liquidity Beta (2)	-0.06	-0.03	0.01	0.08	-0.02	0.08	-0.01	-0.02	-0.02	0.01	0.01	0.00	-0.01	-0.04	0.05	1																		
(48) Liquidity Beta (3)	-0.12	-0.15	-0.23	0.01	-0.02	0.03	0.04	-0.03	0.04	-0.22	0.04	-0.01	-0.02	-0.11	0.13	0.42	1																	
(49) Long-term Reversal (1)	0.14	-0.03	0.22	-0.19	-0.13	-0.03	0.02	-0.09	0.11	0.31	-0.67	-0.12	-0.22	0.20	-0.16	-0.08	-0.13	1																
(50) Long-term Reversal (2)	0.12	0.05	0.34	-0.14	-0.07	0.06	0.08	-0.11	0.14	0.41	-0.59	-0.14	-0.22	0.03	-0.13	-0.03	-0.12	0.85	1															
(51) Long-term Reversal (3)	-0.10	-0.09	-0.39	0.13	0.06	-0.08	-0.10	0.10	-0.13	-0.39	0.56	0.16	0.23	0.04	0.15	-0.02	0.16	-0.76	-0.88	1														
(52) Market Beta (2)	-0.12	-0.72	-0.27	-0.44	-0.65	-0.48	-0.44	-0.51	-0.47	-0.61	0.01	-0.51	-0.46	0.19	-0.11	0.07	0.15	-0.10	-0.17	0.17	1													
(54) Momentum (2)	0.22	-0.13	0.03	-0.06	-0.22	-0.19	-0.16	-0.02	0.09	-0.02	-0.36	-0.07	-0.08	0.18	0.01	-0.03	0.00	0.58	0.45	-0.41	0.09	1												
(59) Profit Margin	0.06	0.60	0.58	0.29	0.48	0.44	0.40	0.24	0.25	0.48	-0.17	0.10	0.06	-0.26	-0.18	0.03	-0.13	0.24	0.33	-0.39	-0.50	-0.05	1											
(60) PPE-to-Assets	-0.04	0.17	0.25	0.12	0.18	0.15	0.14	0.05	0.09	-0.04	-0.07	0.11	0.07	-0.15	-0.04	0.01	-0.01	0.02	0.02	-0.05	-0.08	-0.06	0.19	1										
(61) R&D-to-Assets	0.00	-0.25	0.08	-0.38	-0.32	-0.48	-0.37	-0.40	-0.35	-0.21	-0.09	-0.55	-0.43	0.15	-0.21	-0.06	-0.16	0.07	0.08	-0.11	0.27	0.09	0.05	-0.09	1									
(73) Return Variance (8)	-0.05	-0.65	-0.15	-0.49	-0.62	-0.43	-0.39	-0.51	-0.42	-0.45	-0.24	-0.52	-0.51	0.19	-0.20	0.08	0.04	0.24	0.15	-0.16	0.67	0.26	-0.30	-0.01	0.25	1								
(74) Sales Growth (1)	0.08	0.43	0.14	0.48	0.49	0.22	0.11	0.63	0.39	0.07	0.31	0.58	0.64	-0.25	0.25	0.02	0.03	-0.34	-0.34	0.30	-0.36	-0.12	0.06	0.06	-0.32	-0.42	1							
(75) Sales Growth (2)	0.18	0.42	0.04	0.45	0.50	0.34	0.25	0.57	0.54	0.18	0.11	0.71	0.63	-0.11	0.24	-0.01	0.01	-0.16	-0.15	0.19	-0.43	-0.10	0.02	0.04	-0.37	-0.46	0.66	1						
(77) Sales-to-market equity (1)	-0.01	0.07	-0.20	0.33	0.17	0.31	0.13	0.34	0.18	-0.17	0.36	0.47	0.41	-0.02	0.34	0.07	0.18	-0.45	-0.47	0.50	0.01	-0.20	-0.44	-0.01	-0.54	-0.16	0.38	0.37	1					
(80) Short-run momentum (1)	0.19	0.06	0.14	0.00	0.03	-0.05	-0.04	-0.04	0.13	0.10	-0.20	-0.07	-0.03	0.02	0.01	0.06	-0.01	0.50	0.50	-0.50	-0.08	0.60	0.13	-0.12	0.15	0.06	-0.15	-0.08	-0.27	1				
(81) Short-run momentum (2)	0.11	0.10	0.04	0.10	-0.01	0.01	-0.01	0.08	0.16	0.14	-0.11	0.07	0.04	0.02	0.03	0.14	0.06	0.34	0.35	-0.36	-0.08	0.65	0.05	-0.11	0.00	0.01	0.02	0.04	-0.13	0.73	1			
(82) Short-term Reversal	0.14	-0.07	-0.09	-0.17	-0.03	-0.11	-0.12	-0.22	-0.05	0.10	-0.40	-0.19	-0.09	0.25	-0.15	0.03	-0.10	0.56	0.48	-0.48	-0.02	0.40	0.11	-0.09	0.14	0.20	-0.28	-0.17	-0.34	0.59	0.26	1		
(83) SUE	0.10	0.14	0.22	-0.09	-0.02	0.05	0.06	0.05	0.09	0.43	-0.36	0.01	-0.05	0.05	-0.13	-0.06	-0.16	0.38	0.34	-0.36	-0.19	0.20	0.24	0.05	0.06	0.03	-0.13	-0.10	-0.29	0.17	0.15	0.20	1	
(84) Unexpected Earnings (1)	0.02	0.03	0.10	0.03	0.01	0.03	-0.01	-0.04	-0.02	0.03	-0.06	-0.03	0.00	-0.02	0.00	0.20	0.09	0.14	0.14	-0.16	0.04	0.15	0.05	-0.16	0.10	0.09	-0.04	-0.03	0.00	0.27	0.26	0.09	0.09	1

Table 1.3

Number and percentage of high-low investor sentiment coefficients for 50 trading strategies. This table presents the number and percentage of coefficients that pass either a one-tailed or two-tailed *t*-test after regressing excess portfolio returns on a dummy variable indicating whether the prior period had high investor sentiment. For each of the 50 trading strategies and for each sentiment variable I regress the long leg, short leg, and long-short (hedge) portfolio returns in excess of the 1-month Treasury rate on a dummy variable that takes a value of 1 if the prior value of the investor sentiment index was greater than the median value of this sentiment index over the entire sample period. The regression equation is $R_{i,t} = a + a_H d_{H,t} + \varepsilon_{i,t}$, where $R_{i,t}$ is the excess portfolio return, a is a constant, and $d_{H,t}$ is the high investor sentiment indicator variable. This regression measures the average excess return difference between high and low investor sentiment for each portfolio and was originally used in Stambaugh, Yu, and Yuan (2012). All regressions are estimated using White (1980) standard errors. The original strategies are the 16 trading strategies that appear in Stambaugh, Yu, and Yuan (2012). These variables are Campbell, Hilscher, and Szilagyi's (2008) distress risk; Ohlson's (1980) O-score; net stock issues; Daniel and Titman's Composite equity issues; Sloan (1996) accruals; net operating assets; momentum; gross profitability; asset growth; return on assets; investment-to-assets; a combination strategy that invests equally in the prior variables; market beta; firm size; book-to-market; and Pastor and Stambaugh's (2003) liquidity beta. New strategies are all of the strategies that were not previously tested in Stambaugh, Yu, and Yuan (2012). A description of these strategies is given in Section 2. The 6 sentiment measures are Baker and Wurgler (2006) orthogonalized investor sentiment, Baker and Wurgler (2006) investor sentiment, University of Michigan Consumer Confidence, University of Michigan residual consumer confidence constructed using the 6 Baker and Wurgler (2006) investor sentiment input variables, University of Michigan residual consumer confidence constructed using the 6 Baker and Wurgler (2006) economic growth variables, and University of Michigan residual consumer confidence constructed using economic levels instead of economic growth variables. A detailed description of how these sentiment variables are constructed is given in Section 2.

Panel A. Long leg portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors				After controlling for Fama and French (1993) factors			
				Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	2	14	12.50%	87.50%	3	13	18.75%	81.25%
		New	34	2	32	5.88%	94.12%	5	29	14.71%	85.29%
		Overall	50	4	46	8.00%	92.00%	8	42	16.00%	84.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	0	16	0.00%	100.00%	2	14	12.50%	87.50%
		New	34	0	34	0.00%	100.00%	4	30	11.76%	88.24%
		Overall	50	0	50	0.00%	100.00%	6	44	12.00%	88.00%
(3)	Baker and Wurgler investor sentiment	Original	16	0	16	0.00%	100.00%	3	13	18.75%	81.25%
		New	34	1	33	2.94%	97.06%	6	28	17.65%	82.35%
		Overall	50	1	49	2.00%	98.00%	9	41	18.00%	82.00%
(4)	University of Michigan consumer confidence	Original	16	0	16	0.00%	100.00%	2	14	12.50%	87.50%
		New	34	1	33	2.94%	97.06%	3	31	8.82%	91.18%
		Overall	50	1	49	2.00%	98.00%	5	45	10.00%	90.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	3	13	18.75%	81.25%	0	16	0.00%	100.00%
		New	34	18	16	52.94%	47.06%	1	33	2.94%	97.06%
		Overall	50	21	29	42.00%	58.00%	1	49	2.00%	98.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	2	14	12.50%	87.50%	0	16	0.00%	100.00%
		New	34	11	23	32.35%	67.65%	4	30	11.76%	88.24%
		Overall	50	13	37	26.00%	74.00%	4	46	8.00%	92.00%

Table 1.3 continued

Panel B. Short leg portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors				After controlling for Fama and French (1993) factors			
				Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	12	4	75.00%	25.00%	13	3	81.25%	18.75%
		New	34	19	15	55.88%	44.12%	18	16	52.94%	47.06%
		Overall	50	31	19	62.00%	38.00%	31	19	62.00%	38.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	3	13	18.75%	81.25%	11	5	68.75%	31.25%
		New	34	1	33	2.94%	97.06%	6	28	17.65%	82.35%
		Overall	50	4	46	8.00%	92.00%	17	33	34.00%	66.00%
(3)	Baker and Wurgler investor sentiment	Original	16	8	8	50.00%	50.00%	12	4	75.00%	25.00%
		New	34	9	25	26.47%	73.53%	19	15	55.88%	44.12%
		Overall	50	17	33	34.00%	66.00%	31	19	62.00%	38.00%
(4)	University of Michigan consumer confidence	Original	16	11	5	68.75%	31.25%	12	4	75.00%	25.00%
		New	34	9	25	26.47%	73.53%	12	22	35.29%	64.71%
		Overall	50	20	30	40.00%	60.00%	24	26	48.00%	52.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	14	2	87.50%	12.50%	11	5	68.75%	31.25%
		New	34	29	5	85.29%	14.71%	7	27	20.59%	79.41%
		Overall	50	43	7	86.00%	14.00%	18	32	36.00%	64.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	14	2	87.50%	12.50%	12	4	75.00%	25.00%
		New	34	29	5	85.29%	14.71%	15	19	44.12%	55.88%
		Overall	50	43	7	86.00%	14.00%	27	23	54.00%	46.00%

Table 1.3 continued

Panel C. Long-Short portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors				After controlling for Fama and French (1993) factors			
				Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	10	6	62.50%	37.50%	9	7	56.25%	43.75%
		New	34	9	25	26.47%	73.53%	6	28	17.65%	82.35%
		Overall	50	19	31	38.00%	62.00%	15	35	30.00%	70.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	9	7	56.25%	43.75%	7	9	43.75%	56.25%
		New	34	3	31	8.82%	91.18%	1	33	2.94%	97.06%
		Overall	50	12	38	24.00%	76.00%	8	42	16.00%	84.00%
(3)	Baker and Wurgler investor sentiment	Original	16	12	4	75.00%	25.00%	12	4	75.00%	25.00%
		New	34	10	24	29.41%	70.59%	8	26	23.53%	76.47%
		Overall	50	22	28	44.00%	56.00%	20	30	40.00%	60.00%
(4)	University of Michigan consumer confidence	Original	16	10	6	62.50%	37.50%	10	6	62.50%	37.50%
		New	34	8	26	23.53%	76.47%	4	30	11.76%	88.24%
		Overall	50	18	32	36.00%	64.00%	14	36	28.00%	72.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	9	7	56.25%	43.75%	6	10	37.50%	62.50%
		New	34	7	27	20.59%	79.41%	3	31	8.82%	91.18%
		Overall	50	16	34	32.00%	68.00%	9	41	18.00%	82.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	9	7	56.25%	43.75%	8	8	50.00%	50.00%
		New	34	9	25	26.47%	73.53%	4	30	11.76%	88.24%
		Overall	50	18	32	36.00%	64.00%	12	38	24.00%	76.00%

Table 1.4

Number and percentage of predictive regression coefficients for 50 trading strategies. This table presents the number and percentage of coefficients that pass either a one-tailed or two-tailed *t*-test after regressing excess portfolio returns on lagged investor sentiment. For each of the 50 trading strategies I regress the long leg, short leg, and long-short (hedge) portfolio returns in excess of the 1-month Treasury rate on the lagged level of 1 of the 6 sentiment measures. The regression equation is $R_{i,t} = a + bS_{t-1} + \varepsilon_{i,t}$, where $R_{i,t}$ is the excess portfolio return, a is a constant, and S_{t-1} is the lagged level of the Baker and Wurgler (2006) orthogonalized investor sentiment index, the Baker and Wurgler (2006) investor sentiment index, the University of Michigan Consumer Confidence, or University of Michigan residual consumer confidence constructed using either the 6 Baker and Wurgler input sentiment variables or the growth or level of the 6 economic variables used in Baker and Wurgler (2006). This regression is used to test whether portfolio returns can be predicted using lagged investor sentiment and was originally used in Stambaugh, Yu, and Yuan (2012). All regressions are estimated using White (1980) standard errors. The 16 original trading strategies are Campbell, Hilscher, and Szilagyi's (2008) distress risk; Ohlson's (1980) O-score; net stock issues; Daniel and Titman's composite equity issues; Sloan (1996) accruals; net operating assets; momentum; gross profitability; asset growth; return on assets; investment-to-assets; a combination strategy that invests equally in the prior strategies; market beta; firm size; book-to-market; and Pástor and Stambaugh's (2003) liquidity beta. I refer to any other trading strategy as a new trading strategy. A description of these other strategies is given in section 1.2.2.

Panel A. Long leg portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors				After controlling for Fama and French (1993) factors			
				Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	4	12	25.00%	75.00%	2	14	12.50%	87.50%
		New	34	18	16	52.94%	47.06%	9	25	26.47%	73.53%
		Overall	50	22	28	44.00%	56.00%	11	39	22.00%	78.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	3	13	18.75%	81.25%	2	14	12.50%	87.50%
		New	34	12	22	35.29%	64.71%	3	31	8.82%	91.18%
		Overall	50	15	35	30.00%	70.00%	5	45	10.00%	90.00%
(3)	Baker and Wurgler investor sentiment	Original	16	3	13	18.75%	81.25%	4	12	25.00%	75.00%
		New	34	16	18	47.06%	52.94%	11	23	32.35%	67.65%
		Overall	50	19	31	38.00%	62.00%	15	35	30.00%	70.00%
(4)	University of Michigan consumer confidence	Original	16	0	16	0.00%	100.00%	1	15	6.25%	93.75%
		New	34	1	33	2.94%	97.06%	4	30	11.76%	88.24%
		Overall	50	1	49	2.00%	98.00%	5	45	10.00%	90.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	6	10	37.50%	62.50%	3	13	18.75%	81.25%
		New	34	20	14	58.82%	41.18%	6	28	17.65%	82.35%
		Overall	50	26	24	52.00%	48.00%	9	41	18.00%	82.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	5	11	31.25%	68.75%	1	15	6.25%	93.75%
		New	34	19	15	55.88%	44.12%	3	31	8.82%	91.18%
		Overall	50	24	26	48.00%	52.00%	4	46	8.00%	92.00%

Table 1.4 continued

Panel B. Short leg portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors: Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	After controlling for Fama and French (1993) factors: Number of statistically significant coefficients	Number of statistically insignificant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	13	3	81.25%	18.75%	12	4	75.00%	25.00%
		New	34	25	9	73.53%	26.47%	17	17	50.00%	50.00%
		Overall	50	38	12	76.00%	24.00%	29	21	58.00%	42.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	14	2	87.50%	12.50%	12	4	75.00%	25.00%
		New	34	28	6	82.35%	17.65%	11	23	32.35%	67.65%
		Overall	50	42	8	84.00%	16.00%	23	27	46.00%	54.00%
(3)	Baker and Wurgler investor sentiment	Original	16	13	3	81.25%	18.75%	13	3	81.25%	18.75%
		New	34	22	12	64.71%	35.29%	17	17	50.00%	50.00%
		Overall	50	35	15	70.00%	30.00%	30	20	60.00%	40.00%
(4)	University of Michigan consumer confidence	Original	16	6	10	37.50%	62.50%	12	4	75.00%	25.00%
		New	34	6	28	17.65%	82.35%	13	21	38.24%	61.76%
		Overall	50	12	38	24.00%	76.00%	25	25	50.00%	50.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	14	2	87.50%	12.50%	14	2	87.50%	12.50%
		New	34	30	4	88.24%	11.76%	20	14	58.82%	41.18%
		Overall	50	44	6	88.00%	12.00%	34	16	68.00%	32.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	16	0	100.00%	0.00%	13	3	81.25%	18.75%
		New	34	31	3	91.18%	8.82%	18	16	52.94%	47.06%
		Overall	50	47	3	94.00%	6.00%	31	19	62.00%	38.00%

Table 1.4 continued

Panel C. Long-Short portfolios

	Sentiment measure	Strategy group	Number of strategies	Without controlling for Fama and French (1993) factors: Number of statistically significant coefficients	Without: Number of statistically insignificant coefficients	Without: Percentage of statistically significant coefficients	Without: Percentage of statistically insignificant coefficients	After controlling for Fama and French (1993) factors: Number of statistically significant coefficients	After: Number of statistically insignificant coefficients	After: Percentage of statistically significant coefficients	After: Percentage of statistically insignificant coefficients
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	16	11	5	68.75%	31.25%	11	5	68.75%	31.25%
		New	34	11	23	32.35%	67.65%	8	26	23.53%	76.47%
		Overall	50	22	28	44.00%	56.00%	19	31	38.00%	62.00%
(2)	University of Michigan residual confidence using economic growth	Original	16	11	5	68.75%	31.25%	10	6	62.50%	37.50%
		New	34	6	28	17.65%	82.35%	4	30	11.76%	88.24%
		Overall	50	17	33	34.00%	66.00%	14	36	28.00%	72.00%
(3)	Baker and Wurgler investor sentiment	Original	16	11	5	68.75%	31.25%	11	5	68.75%	31.25%
		New	34	10	24	29.41%	70.59%	9	25	26.47%	73.53%
		Overall	50	21	29	42.00%	58.00%	20	30	40.00%	60.00%
(4)	University of Michigan consumer confidence	Original	16	11	5	68.75%	31.25%	8	8	50.00%	50.00%
		New	34	8	26	23.53%	76.47%	6	28	17.65%	82.35%
		Overall	50	19	31	38.00%	62.00%	14	36	28.00%	72.00%
(5)	University of Michigan residual confidence using economic level variables	Original	16	9	7	56.25%	43.75%	8	8	50.00%	50.00%
		New	34	9	25	26.47%	73.53%	6	28	17.65%	82.35%
		Overall	50	18	32	36.00%	64.00%	14	36	28.00%	72.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	16	10	6	62.50%	37.50%	11	5	68.75%	31.25%
		New	34	11	23	32.35%	67.65%	7	27	20.59%	79.41%
		Overall	50	21	29	42.00%	58.00%	18	32	36.00%	64.00%

Table 1.5

Variables added for correlation thresholds between 0.76 and 0.99. This table lists the variables that are added to the initial list of 42 trading strategies as I vary the correlation threshold between 0.76 and 0.99, inclusive, in increments of 0.01. Starting with 86 different trading strategies, I remove those strategies that have a correlation of 0.75 or above with the 16 original trading strategies. Next, of the remaining new strategies, I remove those that have a correlation of 0.75 or above with the new strategies. For strategies that have a correlation above a given threshold, I remove the strategy that has the highest mean absolute correlation with all of the other strategies. After completing these 2 steps I am left with 42 strategies. I repeat this procedure for correlation thresholds 0.76 through 0.99. If a strategy that was previously removed is no longer removed for a given threshold, then I add this strategy to the list of 42 strategies and use this list of test strategies as the initial strategy list for all correlation thresholds greater than the current threshold. Thus, I am never adding and removing the same strategy for different correlation thresholds.

Correlation when added	Strategy Number	Variable Name
76	44	Investments to Assets (3)
76	48	Liquidity Beta (3)
76	49	Long-term Reversal (1)
76	54	Momentum (2)
77	33	External Finance (1)
77	77	Sales-to-market equity (1)
79	18	Age
79	31	Earnings-to-market equity (2)
82	25	Credit Rating
82	66	Return Variance (1)
83	20	Asset Growth (2)
83	62	Return on Assets (2)
83	79	Share Turnover
84	26	Dividends-to-book equity
85	29	Earnings-to-book equity
85	76	Sales Growth (3)
87	36	Idiosyncratic Risk (1)
88	65	Return on Equity (2)
88	67	Return Variance (2)
88	86	Combination Strategy (2)
90	22	Book-to-market (3)
90	58	Profitability-to-book
91	21	Book-to-market (2)
91	57	O-Score (4)
91	63	Return on Assets (3)
91	64	Return on Equity (1)
94	40	Illiquidity (3)
94	85	Unexpected Earnings (2)
96	68	Return Variance (3)
97	53	Market Beta (3)
98	41	Illiquidity (4)
98	69	Return Variance (4)
98	78	Sales-to-market equity (2)
99	23	Cash flow-to-market equity (1)
99	37	Idiosyncratic Risk (2)
99	70	Return Variance (5)

Table 1.6

Highly correlated strategies. This table lists variables that have a correlation above (0.99) with another strategy already included in the list of test assets.

Strategy Number	Variable Name
28	Dividends-to-price (2)
30	Earnings-to-market equity (1)
38	Illiquidity (1)
39	Illiquidity (2)
55	O-Score (2)
56	O-Score (3)
71	Return Variance (6)
72	Return Variance (7)

Table 1.7

Percentage of significant coefficients using Conditional CAPM. This table shows the percentage of statistically significant investor sentiment coefficients before and after controlling for the conditional CAPM model. Specifically, I estimate the average return difference between high and low sentiment and the predictive sentiment regressions using the following 2 conditional CAPM models:

$$R_{t+1} = a + a_H d_{H,t} + (b_0 + b_1 Div_t + b_2 DEF_t + b_3 TERM_t + b_4 TB_t) r_{m,t+1} + \varepsilon_{t+1} \qquad (14)$$

and

$$R_{t+1} = a + b\, S_t + (c_0 + c_1 Div_t + c_2 DEF_t + c_3 TERM_t + c_4 TB_t) r_{m,t+1} + \varepsilon_{t+1}\ , \qquad (15)$$

where $d_{H,t}$ is a dummy variable indicating if the prior period had high investor sentiment, Div is the 12-month dividend yield, DEF is the default spread, TERM is the term spread, TB is 3-month Treasury bill rate, and r_m is the excess return on the value-weighted market portfolio. This model was previously used in Cooper et al. (2008). The dividend yield is calculated following Fama and French (1988).

Panel A. Percentage of statistically significant high-low sentiment coefficients

	Sentiment measure	Strategy group	Before controlling for Conditional CAPM factors			After controlling for Conditional CAPM factors		
			Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	12.50%	75.00%	62.50%	31.25%	81.25%	56.25%
		New	5.88%	55.88%	26.47%	20.59%	55.88%	26.47%
		Overall	8.00%	62.00%	38.00%	24.00%	64.00%	36.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	0.00%	18.75%	56.25%	12.50%	81.25%	56.25%
		New	0.00%	2.94%	8.82%	17.65%	55.88%	8.82%
		Overall	0.00%	8.00%	24.00%	16.00%	64.00%	24.00%
(3)	Baker and Wurgler investor sentiment	Original	0.00%	50.00%	75.00%	25.00%	81.25%	75.00%
		New	2.94%	26.47%	29.41%	35.29%	58.82%	29.41%
		Overall	2.00%	34.00%	44.00%	32.00%	66.00%	44.00%
(4)	University of Michigan consumer confidence	Original	0.00%	68.75%	62.50%	25.00%	87.50%	68.75%
		New	2.94%	26.47%	23.53%	32.35%	76.47%	26.47%
		Overall	2.00%	40.00%	36.00%	30.00%	80.00%	40.00%
(5)	University of Michigan residual confidence using economic level variables	Original	18.75%	87.50%	56.25%	6.25%	87.50%	56.25%
		New	52.94%	85.29%	20.59%	20.59%	61.76%	17.65%
		Overall	42.00%	86.00%	32.00%	16.00%	70.00%	30.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	12.50%	87.50%	56.25%	0.00%	81.25%	56.25%
		New	32.35%	85.29%	26.47%	11.76%	67.65%	26.47%
		Overall	26.00%	86.00%	36.00%	8.00%	72.00%	36.00%

Table 1.7 continued

Panel B. Percentage of statistically significant predictive regression coefficients

	Sentiment measure	Strategy group	Before controlling for Conditional CAPM factors			After controlling for Conditional CAPM factors		
			Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	25.00%	81.25%	68.75%	18.75%	81.25%	75.00%
		New	52.94%	73.53%	32.35%	41.18%	55.88%	29.41%
		Overall	44.00%	76.00%	44.00%	34.00%	64.00%	44.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	18.75%	87.50%	68.75%	18.75%	87.50%	68.75%
		New	35.29%	82.35%	17.65%	20.59%	76.47%	17.65%
		Overall	30.00%	84.00%	34.00%	20.00%	80.00%	34.00%
(3)	Baker and Wurgler investor sentiment	Original	18.75%	81.25%	68.75%	25.00%	81.25%	68.75%
		New	47.06%	64.71%	29.41%	44.12%	61.76%	29.41%
		Overall	38.00%	70.00%	42.00%	38.00%	68.00%	42.00%
(4)	University of Michigan consumer confidence	Original	0.00%	37.50%	68.75%	18.75%	87.50%	68.75%
		New	2.94%	17.65%	23.53%	23.53%	82.35%	32.35%
		Overall	2.00%	24.00%	38.00%	22.00%	84.00%	44.00%
(5)	University of Michigan residual confidence using economic level variables	Original	37.50%	87.50%	56.25%	31.25%	87.50%	56.25%
		New	58.82%	88.24%	26.47%	29.41%	76.47%	26.47%
		Overall	52.00%	88.00%	36.00%	30.00%	80.00%	36.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	31.25%	100.00%	62.50%	6.25%	87.50%	62.50%
		New	55.88%	91.18%	32.35%	11.76%	76.47%	35.29%
		Overall	48.00%	94.00%	42.00%	10.00%	80.00%	44.00%

Table 1.8

Percentage of significant coefficients using Sibley et al. (2013) investor sentiment. This table presents the percentage of statistically significant coefficients using predicted and residual investor sentiment. Following Sibley et al. (2013), I regress each of the 6 sentiment measures on the 13 macroeconomic, financial, and risk factor variables used in Sibley et al. (2013). The 13 variables are the U.S. unemployment rate, growth rate in inflation, growth rate in consumption, growth rate in disposable personal income, growth rate in industrial production, NBER recession indicator variable, 3-month Treasury bill rate, default spread, term spread, dividend yield, value-weighted market return, stock market volatility, and a liquidity risk factor. The fitted value from these regressions is defined as predicted investor sentiment while the residual is defined as residual investor sentiment.

Panel A. Percentage of statistically significant high-low sentiment coefficients

Panel A.1 Sibley et al. (2013) predicted investor sentiment results

			Without Fama and French (1993) factors			With Fama and French (1993) factors		
	Sentiment measure	Strategy group	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	31.25%	81.25%	56.25%	18.75%	75.00%	62.50%
		New	52.94%	85.29%	14.71%	20.59%	47.06%	11.76%
		Overall	46.00%	84.00%	28.00%	20.00%	56.00%	28.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	56.25%	100.00%	56.25%	25.00%	25.00%	31.25%
		New	55.88%	97.06%	17.65%	8.82%	8.82%	8.82%
		Overall	56.00%	98.00%	30.00%	14.00%	14.00%	16.00%
(3)	Baker and Wurgler investor sentiment	Original	31.25%	81.25%	56.25%	31.25%	75.00%	62.50%
		New	50.00%	82.35%	20.59%	26.47%	64.71%	11.76%
		Overall	44.00%	82.00%	32.00%	28.00%	68.00%	28.00%
(4)	University of Michigan consumer confidence	Original	12.50%	81.25%	50.00%	12.50%	31.25%	43.75%
		New	26.47%	73.53%	23.53%	17.65%	32.35%	14.71%
		Overall	22.00%	76.00%	32.00%	16.00%	32.00%	24.00%
(5)	University of Michigan residual confidence using economic level variables	Original	0.00%	6.25%	56.25%	18.75%	68.75%	37.50%
		New	0.00%	0.00%	17.65%	23.53%	23.53%	17.65%
		Overall	0.00%	2.00%	30.00%	22.00%	38.00%	24.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	6.25%	37.50%	50.00%	6.25%	31.25%	43.75%
		New	5.88%	47.06%	29.41%	14.71%	26.47%	20.59%
		Overall	6.00%	44.00%	36.00%	12.00%	28.00%	28.00%

Table 1.8 continued

Panel A.2 Sibley et al. (2013) residual investor sentiment results

	Sentiment measure	Strategy group	Without Fama and French (1993) factors			With Fama and French (1993) factors		
			Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	31.25%	0.00%	25.00%	12.50%	25.00%	25.00%
		New	35.29%	0.00%	29.41%	14.71%	23.53%	26.47%
		Overall	34.00%	0.00%	28.00%	14.00%	24.00%	26.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	0.00%	25.00%	43.75%	0.00%	43.75%	18.75%
		New	0.00%	8.82%	26.47%	5.88%	17.65%	14.71%
		Overall	0.00%	14.00%	32.00%	4.00%	26.00%	16.00%
(3)	Baker and Wurgler investor sentiment	Original	75.00%	0.00%	6.25%	6.25%	18.75%	18.75%
		New	67.65%	0.00%	17.65%	5.88%	17.65%	29.41%
		Overall	70.00%	0.00%	14.00%	6.00%	18.00%	26.00%
(4)	University of Michigan consumer confidence	Original	0.00%	0.00%	43.75%	0.00%	43.75%	18.75%
		New	0.00%	0.00%	20.59%	0.00%	17.65%	8.82%
		Overall	0.00%	0.00%	28.00%	0.00%	26.00%	12.00%
(5)	University of Michigan residual confidence using economic level variables	Original	0.00%	0.00%	25.00%	0.00%	31.25%	6.25%
		New	0.00%	5.88%	23.53%	0.00%	14.71%	11.76%
		Overall	0.00%	4.00%	24.00%	0.00%	20.00%	10.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	0.00%	43.75%	50.00%	0.00%	81.25%	50.00%
		New	0.00%	14.71%	26.47%	8.82%	55.88%	17.65%
		Overall	0.00%	24.00%	34.00%	6.00%	64.00%	28.00%

Table 1.8 continued

Panel B. Percentage of statistically significant predictive regression coefficients

Panel B.1 Sibley et al. (2013) predicted investor sentiment results

	Sentiment measure	Strategy group	Without Fama and French (1993) factors			With Fama and French (1993) factors		
			Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	56.25%	93.75%	62.50%	25.00%	75.00%	50.00%
		New	76.47%	91.18%	23.53%	32.35%	50.00%	17.65%
		Overall	70.00%	92.00%	36.00%	30.00%	58.00%	28.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	31.25%	87.50%	62.50%	18.75%	75.00%	56.25%
		New	58.82%	85.29%	17.65%	20.59%	35.29%	14.71%
		Overall	50.00%	86.00%	32.00%	20.00%	48.00%	28.00%
(3)	Baker and Wurgler investor sentiment	Original	50.00%	87.50%	62.50%	25.00%	75.00%	62.50%
		New	79.41%	91.18%	17.65%	41.18%	67.65%	17.65%
		Overall	70.00%	90.00%	32.00%	36.00%	70.00%	32.00%
(4)	University of Michigan consumer confidence	Original	0.00%	18.75%	50.00%	12.50%	56.25%	50.00%
		New	0.00%	14.71%	17.65%	23.53%	32.35%	11.76%
		Overall	0.00%	16.00%	28.00%	20.00%	40.00%	24.00%
(5)	University of Michigan residual confidence using economic level variables	Original	0.00%	62.50%	62.50%	31.25%	81.25%	62.50%
		New	0.00%	23.53%	17.65%	44.12%	70.59%	17.65%
		Overall	0.00%	36.00%	32.00%	40.00%	74.00%	32.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	18.75%	68.75%	43.75%	6.25%	25.00%	12.50%
		New	32.35%	55.88%	26.47%	14.71%	29.41%	17.65%
		Overall	28.00%	60.00%	32.00%	12.00%	28.00%	16.00%

Table 1.8 continued

Panel B.2 Sibley et al. (2013) residual investor sentiment results

	Sentiment measure	Strategy group	Without Fama and French (1993) factors: Long leg	Without Fama and French (1993) factors: Short leg	Without Fama and French (1993) factors: Long-Short	With Fama and French (1993) factors: Long leg	With Fama and French (1993) factors: Short leg	With Fama and French (1993) factors: Long-Short
(1)	Baker and Wurgler orthogonalized investor sentiment	Original	0.00%	0.00%	43.75%	12.50%	50.00%	62.50%
		New	0.00%	5.88%	23.53%	11.76%	32.35%	29.41%
		Overall	0.00%	4.00%	30.00%	12.00%	38.00%	40.00%
(2)	University of Michigan residual confidence using economic growth variables	Original	0.00%	0.00%	12.50%	0.00%	18.75%	12.50%
		New	0.00%	0.00%	5.88%	2.94%	8.82%	5.88%
		Overall	0.00%	0.00%	8.00%	2.00%	12.00%	8.00%
(3)	Baker and Wurgler investor sentiment	Original	0.00%	0.00%	43.75%	6.25%	43.75%	50.00%
		New	0.00%	0.00%	17.65%	8.82%	29.41%	23.53%
		Overall	0.00%	0.00%	26.00%	8.00%	34.00%	32.00%
(4)	University of Michigan consumer confidence	Original	0.00%	0.00%	25.00%	0.00%	12.50%	25.00%
		New	0.00%	0.00%	8.82%	0.00%	11.76%	8.82%
		Overall	0.00%	0.00%	14.00%	0.00%	12.00%	14.00%
(5)	University of Michigan residual confidence using economic level variables	Original	12.50%	62.50%	31.25%	6.25%	12.50%	12.50%
		New	5.88%	47.06%	17.65%	0.00%	8.82%	5.88%
		Overall	8.00%	52.00%	22.00%	2.00%	10.00%	8.00%
(6)	University of Michigan residual confidence using sentiment variables	Original	6.25%	81.25%	68.75%	0.00%	68.75%	56.25%
		New	8.82%	58.82%	23.53%	5.88%	47.06%	17.65%
		Overall	8.00%	66.00%	38.00%	4.00%	54.00%	30.00%

Table 1.9

Percentage of significant coefficients using Huang et al. (2015) sentiment measures. This table presents the percentage of statistically significant coefficients using raw Huang et al. (2015) aligned investor sentiment, predicted Huang et al. (2015) aligned investor sentiment, and residual Huang (2015) aligned investor sentiment. Raw Huang (2015) aligned investor sentiment is constructed by applying partial least squares to the Baker and Wurgler (2006) investor sentiment variables. I obtain this measure directly from Goufu Zhou's website. Predicted and residual Huang (2015) aligned investor sentiment are constructed following the methodology used in Sibley et al. (2013). Specifically, predicted Huang et al. (2015) aligned investor sentiment is the fitted value from regressing the raw Huang et al. (2015) aligned investor sentiment index on the 13 financial variables used in Sibley et al. (2013). Residual Huang et al. (2015) aligned investor sentiment is the residual from regressing the raw Huang et al. (2015) aligned investor sentiment index on the 13 financial variables used in Sibley et al. (2013).

Panel A. Percentage of statistically significant high-low sentiment coefficients

		Without Fama and French (1993) factors			With Fama and French (1993) factors		
Sentiment measure	Strategy group	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Huang et al. (2015) aligned investor sentiment	Original	75.00%	100.00%	62.50%	6.25%	68.75%	25.00%
	New	79.41%	94.12%	29.41%	5.88%	35.29%	17.65%
	Overall	78.00%	96.00%	40.00%	6.00%	46.00%	20.00%
Predicted Huang et al. (2015) aligned investor sentiment	Original	62.50%	100.00%	56.25%	12.50%	68.75%	37.50%
	New	91.18%	91.18%	17.65%	11.76%	44.12%	8.82%
	Overall	82.00%	94.00%	30.00%	12.00%	52.00%	18.00%
Residual Huang et al. (2015) aligned investor sentiment	Original	6.25%	50.00%	31.25%	12.50%	0.00%	6.25%
	New	11.76%	52.94%	41.18%	2.94%	0.00%	11.76%
	Overall	10.00%	52.00%	38.00%	6.00%	0.00%	10.00%

Table 1.9 continued

Panel B. Percentage of statistically significant predictive regression coefficients

Sentiment measure	Strategy group	Without Fama and French (1993) factors			With Fama and French (1993) factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Huang et al. (2015) aligned investor sentiment	Original	93.75%	100.00%	68.75%	6.25%	37.50%	50.00%
	New	91.18%	88.24%	32.35%	14.71%	35.29%	14.71%
	Overall	92.00%	92.00%	44.00%	12.00%	36.00%	26.00%
Predicted Huang et al. (2015) aligned investor sentiment	Original	56.25%	93.75%	56.25%	25.00%	56.25%	31.25%
	New	76.47%	91.18%	14.71%	29.41%	47.06%	14.71%
	Overall	70.00%	92.00%	28.00%	28.00%	50.00%	20.00%
Residual Huang et al. (2015) aligned investor sentiment	Original	50.00%	81.25%	62.50%	6.25%	12.50%	31.25%
	New	64.71%	76.47%	35.29%	8.82%	5.88%	17.65%
	Overall	60.00%	78.00%	44.00%	8.00%	8.00%	22.00%

Table 1.10

Simulation Results. This table presents the percentage of statistically significant investor sentiment coefficients from simulated long, short, and long-short portfolios. Each June, stocks are randomly assigned to 1 of 10 decile portfolios. Value-weighted returns are then calculated from July of year *t* until June of year *t+1*. The decile with the highest average return is defined as the long leg, the decile with the lowest average return is defined as the short leg, and the long-short portfolio is calculated as the difference between the long leg and short leg returns. I then estimate the difference in returns between high and low sentiment and the predictive regression coefficients for the long leg, short leg, and long-short portfolio using each of the 18 sentiment measures. I repeat this process 10,000 times.

Panel A. Percentage of signficant high-low coefficients

Panel A.1. Original Sentiment measures

	Without Fama and French (1993) factors			With Fama and French (1993) factors		
Sentiment Measure	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1) Baker Wurgler OIS	0.01%	1.23%	7.74%	2.95%	10.58%	8.05%
(2) UMICH RES GDP GROWTH	0.00%	0.08%	10.31%	2.71%	12.48%	10.70%
(3) Baker Wurgler IS	0.00%	0.00%	8.78%	3.08%	10.55%	8.82%
(4) UMICH	0.01%	1.20%	9.32%	6.20%	23.83%	10.05%
(5) UMICH RES GDP LEVELS	6.78%	33.59%	4.97%	3.59%	7.65%	4.71%
(6) UMICH RES Sent Variables	12.73%	72.77%	11.98%	9.81%	40.97%	11.98%
(7) Huang et al. AIS	80.24%	99.31%	10.66%	2.50%	9.43%	10.30%

Panel A.2. Predicted Sentiment Measures

	Without Fama and French (1993) factors			With Fama and French (1993) factors		
Sentiment Measure	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1) Baker Wurgler OIS	6.53%	47.65%	8.77%	4.13%	15.50%	8.79%
(2) UMICH RES GDP GROWTH	71.07%	97.71%	10.91%	3.24%	9.74%	10.20%
(3) Baker Wurgler IS	4.61%	39.40%	8.94%	8.04%	25.22%	9.58%
(4) UMICH	7.19%	47.34%	8.55%	6.88%	20.51%	8.40%
(5) UMICH RES GDP LEVELS	0.00%	0.00%	7.78%	4.67%	13.51%	8.25%
(6) UMICH RES Sent Variables	0.04%	2.43%	8.82%	3.87%	15.86%	9.74%
(7) Huang et al. AIS	56.61%	94.13%	9.45%	3.76%	15.15%	9.84%

Table 1.10 continued

Panel A.3. Residual Sentiment Measures

Sentiment Measure	Without Fama and French (1993) factors			With Fama and French (1993) factors		
	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1) Baker Wurgler OIS	39.29%	0.00%	7.05%	5.67%	1.19%	6.72%
(2) UMICH RES GDP GROWTH	0.01%	0.77%	10.27%	7.60%	18.52%	9.96%
(3) Baker Wurgler IS	98.99%	0.00%	6.32%	7.15%	0.89%	6.02%
(4) UMICH	0.00%	0.00%	8.36%	6.18%	16.79%	8.04%
(5) UMICH RES GDP LEVELS	0.01%	0.20%	3.95%	3.47%	3.97%	4.06%
(6) UMICH RES Sent Variables	0.01%	2.42%	8.40%	7.72%	20.49%	8.19%
(7) Huang et al. AIS	3.62%	41.93%	8.37%	6.29%	1.16%	7.35%

Panel B. Percentage of signficant predictive regression coefficients

Panel B.1. Original sentiment measures

Sentiment measure	Without Fama and French (1993) factors			With Fama and French (1993) factors		
	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1) Baker Wurgler OIS	3.20%	40.34%	9.67%	2.51%	12.58%	9.83%
(2) UMICH RES GDP GROWTH	5.33%	50.78%	12.99%	3.03%	21.39%	13.47%
(3) Baker Wurgler IS	0.33%	13.29%	8.46%	2.82%	11.96%	8.83%
(4) UMICH	0.00%	0.22%	10.20%	6.68%	30.63%	11.27%
(5) UMICH RES GDP LEVELS	19.14%	56.40%	6.52%	8.37%	17.89%	6.24%
(6) UMICH RES Sent Variables	69.16%	97.33%	10.66%	8.98%	35.27%	11.08%
(7) Huang et al. AIS	99.86%	100.00%	11.45%	1.38%	6.69%	11.15%

Panel B.2. Predicted sentiment measures

Sentiment measure	Without Fama and French (1993) factors			With Fama and French (1993) factors		
	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1) Baker Wurgler OIS	24.37%	77.66%	8.16%	5.94%	18.81%	7.82%
(2) UMICH RES GDP GROWTH	33.80%	85.31%	8.41%	7.31%	23.19%	8.58%
(3) Baker Wurgler IS	0.00%	0.18%	9.89%	6.13%	28.95%	10.74%
(4) UMICH	2.66%	34.61%	9.10%	4.89%	23.10%	10.54%
(5) UMICH RES GDP LEVELS	32.48%	90.12%	14.73%	2.43%	18.33%	14.83%
(6) UMICH RES Sent Variables	0.00%	0.61%	7.76%	7.63%	18.13%	7.91%
(7) Huang et al. AIS	33.72%	83.07%	6.62%	4.16%	15.13%	6.82%

Table 1.10 continued

Panel B.3. Residual sentiment measures

	Sentiment measure	Without Fama and French (1993) factors			With Fama and French (1993) factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
(1)	Baker Wurgler OIS	0.00%	0.00%	8.53%	2.66%	4.05%	8.86%
(2)	UMICH RES GDP GROWTH	0.00%	0.00%	6.67%	6.48%	11.72%	6.99%
(3)	Baker Wurgler IS	0.00%	0.00%	6.65%	2.69%	2.50%	6.91%
(4)	UMICH	0.00%	0.00%	6.83%	4.38%	9.57%	7.21%
(5)	UMICH RES GDP LEVELS	0.95%	10.97%	3.94%	3.38%	7.01%	3.91%
(6)	UMICH RES Sent Variables	8.27%	51.11%	9.55%	9.58%	24.44%	9.08%
(7)	Huang et al. AIS	90.35%	99.79%	11.77%	3.54%	2.32%	11.12%

Figure 1.1

Acceptance rates using Baker Wurgler (2006) orthogonalized investor sentiment. This figure reports the acceptance rates for 4 different tests as the correlation cutoff threshold is varied from 0.75 to 1.00 in increments of 0.01. The acceptance rate is defined as the number of coefficients that are statistically significant using a 1 tailed *t*-test, H_0: $\mu \leq 0$, divided by the total number of coefficients. As I vary the correlation cutoff threshold from 0.75 to 1.00, the number of strategies tested increases from 43 to 86. In Panels A and B, I present the acceptance rates for the coefficients testing whether the difference following high and low investor sentiment for the long-short strategies is statistically positive with and without the Fama and French (1993) factors. In Panels C and D, I present the acceptance rates for predictive regression of long-short portfolio returns on lagged investor sentiment with and without controlling for the returns on the Fama and French (1993) factors. Original Strategies are the 16 strategies used in Stambaugh, Yu, and Yuan (2012), New Strategies are any strategy not used in Stambaugh, Yu, and Yuan (2012), and All Strategies are all of the strategies tested. I conduct these tests using the Baker and Wurgler (2006) orthogonalized investor sentiment index as the measure of investor sentiment.

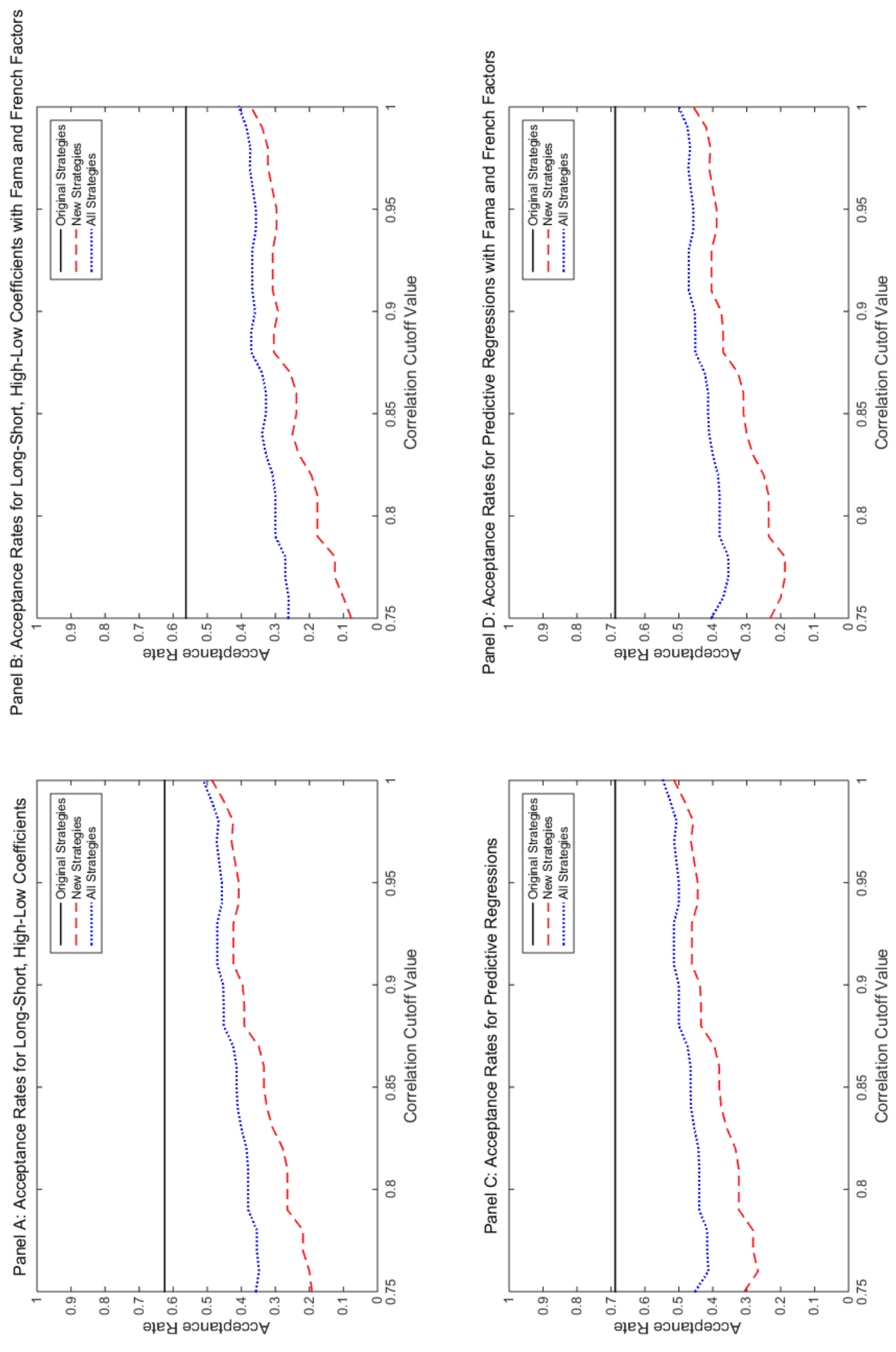
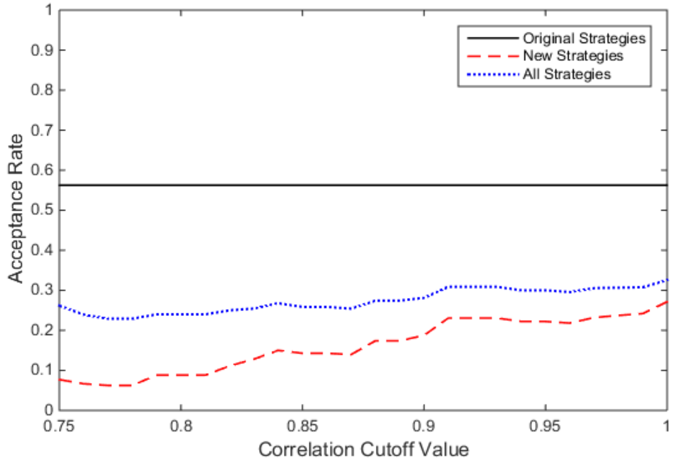

Panel A: Acceptance Rates for Long-Short, High-Low Coefficients
Panel B: Acceptance Rates for Long-Short, High-Low Coefficients with Fama and French Factors
Panel C: Acceptance Rates for Predictive Regressions
Panel D: Acceptance Rates for Predictive Regressions with Fama and French Factors
Original Strategies
New Strategies
All Strategies
Acceptance Rate
Correlation Cutoff Value
0
0.1
0.2
0.3
0.4
0.5
0.6
0.7
0.8
0.9
1
0.75
0.8
0.85
0.9
0.95

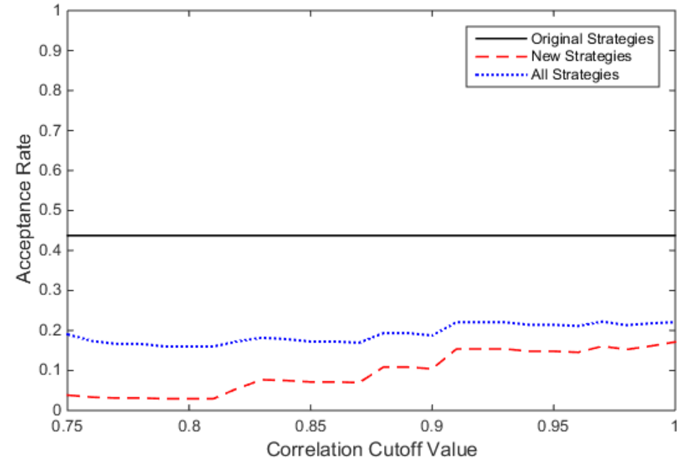
Figure 1.2

Acceptance rates using University of Michigan residual consumer confidence. This table reports the acceptance rates for 4 different tests as the correlation cutoff threshold is varied from 0.75 to 1.00 in increments of 0.01. The acceptance rate is defined as the number of coefficients that are statistically significant using a 1 tailed *t*-test, H_0: $\mu \leq 0$, divided by the total number of coefficients. As we vary the correlation cutoff threshold from 0.75 to 1.00, the number of strategies tested increases from 43 to 86. Panels A and B present the acceptance rates for the coefficients testing whether the difference following high and low investor sentiment for the long-short strategies is statistically positive with and without the Fama and French (1993) factors. Panels C and D present the acceptance rates for predictive regression of long-short portfolio returns on lagged investor sentiment with and without controlling for the returns on the Fama and French (1993) factors. Original Strategies are the 16 strategies used in Stambaugh, Yu, and Yuan (2012), New Strategies are any strategy not used in Stambaugh, Yu, and Yuan (2012), and All Strategies are all of the strategies tested. I conduct these tests using University of Michigan residual consumer confidence. Residual consumer confidence is the residual from the following regression: $\text{UMICH}_t = \alpha + \beta_1\text{Growth\_Indpro}_t + \beta_2\text{Growth\_Consdur}_t + \beta_3\text{Growth\_Consnon}_t + \beta_4\text{Growth\_Consserv}_t + \beta_5 \textit{Growth\_employ}_t + \beta_6 \textit{Recess}_t + \varepsilon_t$, where *UMICH* is the value of the University of Michigan consumer confidence survey, *Growth_Indpro* is the growth of industrial production, *Growth_Consdur* is the growth of durable consumption, *Growth_Consnon* is the growth of nondurable consumption, *Growth_Consserv* is the growth of service consumption, *Growth_employ* is the growth of employment, and *Recess* is a dummy variable for National Bureau of Economic Research recessions.

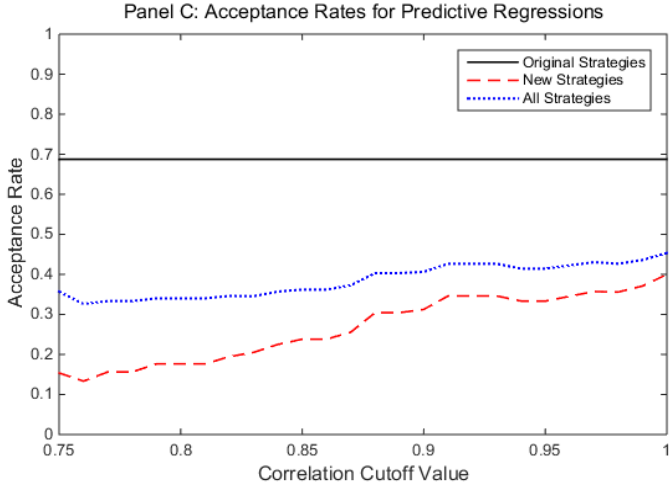
Panel A: Acceptance Rates for Long-Short, High-Low Coefficients



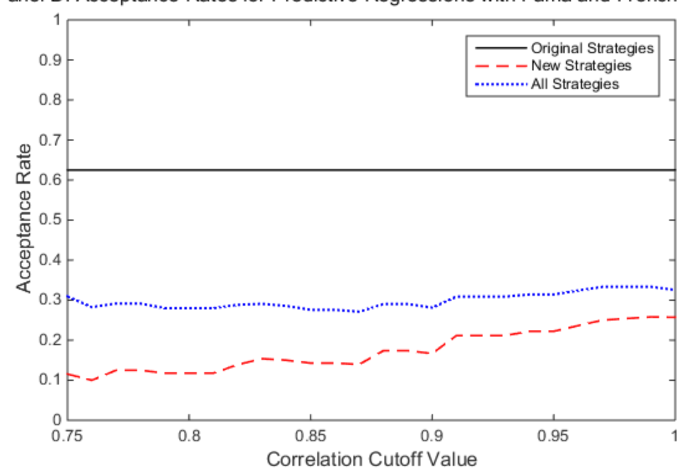
Panel B: Acceptance Rates for Long-Short, High-Low Coefficients with Fama and French Factors



Panel C: Acceptance Rates for Predictive Regressions



Panel D: Acceptance Rates for Predictive Regressions with Fama and French Factors



CHAPTER 2

INVESTOR SENTIMENT, PROFITABLE TRADING STRATEGIES, AND SHORT SALE CONSTRAINTS

There is a growing debate of whether the returns to profitable trading strategies are due to short sale constraints. Baker and Wurgler (2006) construct an investor sentiment index and find that hard-to-value firms are affected by investor sentiment. Baker and Wurgler (2006) state that hard-to-value firms typically have hard-to-short securities. Stambaugh, Yu, and Yuan (2012b) present evidence that the short leg of profitable trading strategies has a higher return following low sentiment and each long-short trading strategy is more profitable following high sentiment. These results imply that the returns to profitable trading strategies are due to short sale constraints. However, recently Bulsiewicz (2013) showed that there is a weak relation between investor sentiment and a large collection of cross-sectional anomalies suggesting that the returns to profitable trading strategies are not due to short sale constraints.

In this paper I directly test whether profitable trading strategies conform to Miller's (1977) hypothesis. Miller (1977) hypothesizes that if there are heterogeneous beliefs in the market, a security that is hard-to-short can become overvalued when investors are optimistic. I assess whether the average firm in these strategies is hard-to-short, if the securities in the short leg are harder-to-short than the securities in the long leg, if there is wider dispersion in beliefs following high sentiment, and if the average security in the long leg and short leg portfolios becomes overvalued following high sentiment.

First, I assess whether or not the short leg is harder-to-short than the long leg and if the average security in the 50 trading strategies considered here is hard-to-short. I find that each strategy invests a small amount in hard-to-short securities and the short leg only invests slightly more than the long leg in hard-to-short securities. Specifically, using equally-weighted portfolios, the long leg invests around 17% in hard-to-short securities, while the short leg invests around 21% in hard-to-short securities. Even less is invested in hard-to-short securities using value-weighted portfolios. On average only 10% of the long leg and 15% of the short leg of each strategy is invested in hard-to-short securities. Further, the difference in weight in hard-to-short securities between high and low sentiment states is less than 2%.

Next, I investigate whether the average security in these strategies is hard-to-short. First, using Amihud's (2002) illiquidity measure, I find that both the long leg and short leg are more liquid following high sentiment than following low sentiment. However, the short leg is not more illiquid than the long leg. I further investigate these results using daily trading volume, dollar trading volume, and share turnover. I find that each trading strategy is more heavily traded following high sentiment than following low sentiment. Using equally-weighted portfolios, the short leg has around \$3 million more trading volume following high sentiment and the long leg has around \$4 million more trading volume following high sentiment; using value-weighted portfolios, the short leg has around \$45 million more trading volume per day following high sentiment while the long leg has around \$53 million more trading volume per day following high sentiment.

Additional tests indicate that the short leg has slightly higher trading costs than the long leg, but there is not a large difference in trading costs across sentiment states. Furthermore, there is not a large difference in the number of zero trading days between the long and short leg portfolios. Using equally-weighted portfolios, the average security in the long leg has a Pastor and Stambaugh (2003) liquidity beta that is not statistically different from 0 while the average security in the short leg has a negative Pastor and Stambaugh (2003) liquidity beta. However, using value-weighted portfolios, the long leg has a Pastor and Stambaugh (2003) liquidity beta that is negative following high sentiment and statistically 0 following low sentiment, while the short leg has a Pastor and Stambaugh (2003) liquidity beta that is statistically 0. Thus, the relation between investor sentiment and profitable trading strategies does not appear to be due to differences in liquidity betas.

I also assess whether the short leg is harder to short than the long leg using idiosyncratic risk, institutional ownership, and short interest. However, I find that the average security in the short leg has similar idiosyncratic risk, institutional ownership, and short interest as the average security in the long leg. Furthermore, I find that there is a large difference in institutional ownership between high and low sentiment states. Institutional ownership is around 9 to 10 percentage points higher following low sentiment using equally-weighted portfolios and around 6 to 7 percentage points higher following low sentiment using value-weighted portfolios. This effect remains even after controlling for market wide ownership and controlling for ownership of firms in similar size deciles. Further tests reveal that this result is driven by mutual funds, hedge funds, and other institutions, while banks and insurance companies maintain their ownership levels across sentiment states.

Miller's (1977) hypothesis requires for there to be wide dispersion in beliefs. Using the average daily return variance and analysts' forecast dispersion, I find that the short leg has higher dispersion in beliefs especially following high sentiment. Thus the short leg conforms to this portion of Miller's hypothesis.

In order to conform to Miller's (19770 hypothesis, the short leg has to become overvalued relative to the average valuation in the market following high sentiment. I find weak evidence in favor of this hypothesis. First, analysts do not view the average security in the short leg as being more overvalued than the average security in the long leg. I construct analysts' expected returns using analysts' median price target and find that they expect the average security in the short leg to earn a higher return than the average security in the long leg. Furthermore, there is not a statistical difference in their average recommendation for the average security in the long leg and short leg portfolios. I also measure overvaluation using book-to-market ratios, but I do not find a material difference between the long leg and the short leg.

As a final test of the Miller's (1977) overvaluation hypothesis, I measure overvaluation using intrinsic value-to-market equity ratios. Intrinsic value is calculated using Ohlson's (1995) residual income model. Previously, it was shown in Frankel and Lee (1998) that intrinsic value-to-market equity ratios are a good measure of mispricing. Using, intrinsic value-to-market equity ratios, I find that the short leg is generally fairly valued relative to the long leg.

Overall, the results indicate that the average security in the short leg of these strategies is not hard-to-short and does not become overvalued following high sentiment. Given that each strategy only invests a small amount in hard-to-short securities, I directly assess whether there is a relation between investor sentiment and hard-to-short securities.

However, the results indicate that there is still only a weak relation between investor sentiment and hard-to-short securities.

These results contribute to the literature by showing that profitable trading strategies do not conform to Miller's (1977) hypothesis, and thus, the relation between investor sentiment and profitable trading strategies are likely not due to short sale constraints. Further, these results suggest that hard-to-short securities are not greatly affected by investor sentiment. Therefore, any relation found between investor sentiment and profitable trading strategies is likely not due to short sale constraints. Additionally, my results indicate that the relation between investor sentiment and some profitable trading strategies may be related to illiquidity and institutional ownership.

The rest of this paper is organized as follows: Section 2.1 reviews the literature, Section 2.2 describes the data and methodology, Section 2.3 presents the results, and Section 2.4 concludes.

2.1 Literature Review

This work is most closely related to the literature showing that stock returns are affected by investor sentiment. Baker and Wurgler (2006) construct a composite sentiment index and show that certain firms are influenced by investor sentiment. A similar finding was found in Livnat and Petrovits (2009) who find that investor sentiment affects the returns to strategies that trade on earnings and accruals. This evidence is extended in Baker, Wurgler, and Yuan (2012) who show that investor sentiment affects stock returns outside the United States. Based on the theory developed by Miller (1977), Stambaugh et al. (2012b) argue that firms in the short leg could be hard-to-short and as a result these firms could become overvalued (relative to the average valuation in the market) following high sentiment. They present compelling evidence that this is indeed the case; firms in the short leg have lower returns following high sentiment and the trading strategies are more profitable following high sentiment. Their results are supported by results presented in Stambaugh et al. (2014). However, Bulsiewicz (2013) finds much weaker support for this argument after expanding the number of strategies tested. He finds that there is a weak relation between investor sentiment and 34 additional common strategies and a weak relation between investor sentiment and simulated profitable strategies.

There has been additional scholarly work on investor sentiment and stock market returns. Tetlock (2007) found that the sentiment of the media affects stock market returns while Kumar and Lee (2006) found that retail investors trade in the same direction as one another; when one retail investor buys other retail investors buy and vice versa. Other papers have focused on investor sentiment and the tradeoff between risk and return, how to measure investor sentiment, interaction between investor sentiment and analysts' forecasts, and investor sentiment and market irregularities (see for example Ben-Rephael et al. (2012), Hribar and McInnis (2012), Lee et al. (1991), and Yu and Yuan (2011)).

My work is also related to the literature that argues that the returns to profitable trading strategies are due to mispricing. Originally, Lakonishok, Shleifer, and Vishny (1994) argued that certain trading strategies, i.e., the strategy that trades on book-to-market ratios, are profitable because they purchase securities that are undervalued and sell securities that are overvalued. Cooper et al. (2004) found evidence consistent with this explanation when they investigated price momentum and whether the prior market had high or low returns. Some financial scholars argued that mispricing in the market could exist if arbitrageurs are not able to trade on the mispricing, i.e., there are limits to arbitrage.

(De Long et al. (1990), Pontiff (1996), and Shleifer and Vishny (1997)) Later work has aimed at testing whether this explanation can at least partially explain the returns to profitable trading strategies. (Cohen et al. (2007), Lam and Wei (2011), and Mashruwala et al. (2006)) Other research in this area includes: Doukas et al. (2010), Li and Zhang (2010), Sadka and Scherbina (2007), and Stambaugh et al. (2012a).

One trading friction that could prevent securities from accurately reflecting fundamentals is short sale loan fees. As discussed in Miller (1977), securities that are hard-to-short may become mispriced. The topic of short selling and stock market returns has been the focus of a number of studies. Using institutional ownership as a proxy for short sale constraints, Nagel (2005) finds that certain trading strategies are more profitable for firms that are thought to be hard-to-short. Asquith, Pathak, and Ritter (2005) sort firms on institutional ownership and short interest and find that firms with low institutional ownership or high short interest have lower returns than other firms and find that firms thought to be hard-to-short underperform other securities. Consistent with D'Avolio (2002), they also find that the majority of firms are not hard-to-short. Ali and Trombley (2006) investigate the relation between short sale constraints and momentum profits and find that momentum profits are positively related to short sale constraints. Boehme et al. (2006) find evidence consistent with Miller's (1977) argument that if a security is hard-to-short than it may become overvalued; they find securities with high dispersion in investor's valuations and high short sale constraints underperform other securities. In other work, Diether et al. (2009) investigate the trading practices of short sellers and Israel and Moskowitz (2013) present evidence that a large portion of the size, value, and momentum profits come from the long leg of each strategy. Further, they find that the returns to these strategies are not greatly affected by trading costs and institutional ownership. Unlike Israel and Moskowitz (2013), I find that there is a relation between institutional holdings and profitable trading strategies. I find that financial institutions hold a higher percentage of the shares outstanding of short leg firms during periods when these portfolios earn a higher return, namely following low sentiment.

One strand of the asset pricing literature investigates whether these trading strategies are still profitable after controlling for trading costs. For example, Korajczyk and Sadka (2004) and Lesmond et al. (2004) investigated the profitability of the momentum trading strategy originally documented by Jegadeesh and Titman (1993) and found mixed results on whether this trading strategy is still profitable after controlling for trading costs. Earlier work by Stoll and Whaley (1983) provided evidence that the small firm effect originally documented by Banz (1981) and Reinganum (1981) is at least partially explained by trading costs. In more recent work, Ng et al. (2008) found that firms with high trading costs respond less to earnings announcements and the returns to the post-earnings announcement drift trading strategy is reduced by trading costs. I add to this literature by showing for a collection of trading strategies, trading costs reduce the high returns following low sentiment.

The work presented here is also related to the literature on stock market liquidity and asset pricing. Acharya and Pedersen (2005) present a theoretical model where liquidity risk is a priced risk factor. They find that periods of illiquidity should be followed by higher returns. Likewise, Hasbrouck (2009) finds that returns are increasing in trading costs and Baker and Stein (2004) present a theoretical model that explains why returns are increasing in liquidity and trading costs. Bekaert et al. (2007) expand these results to emerging markets and find a similar relation between liquidity and returns in these markets. In a related study, Chordia et al. (2008) find that liquidity helps to improve markets by increasing arbitrage activity and making prices move closer to a random walk. Pastor and Stambaugh (2003) find that firms whose returns are highly sensitive to changes in liquidity earn higher returns than firms that are less sensitive. In a later study, Sadka (2010) found that hedge funds that are more sensitive to liquidity risk outperform other funds that are less sensitive to liquidity risk. Additional work in this literature, such as Avramov et al. (2013), Chordia et al. (2009), and Sadka (2006), has looked for a link between profitable trading strategies and liquidity. Generally, these studies have found that liquidity helps to explain the returns to these strategies. I add to this literature by showing that the short leg of certain trading strategies is more illiquid than the long leg of these trading strategies and that the short leg is more illiquid following low sentiment.

There is also a body of literature investigating how financial institutions trade. Jiang (2010) investigates the book-to-market effect and institutional investors and finds that financial institutions trade on the intangible information measure presented in Daniel and Titman (2006) and that financial institutions are trading on book-to-market ratios. Campbell et al. (2009) look at how financial institutions trade on a daily basis and present evidence that institutions are trading on momentum and earnings announcements. I contribute to this literature by showing that financial institutions are trading on profitable trading strategies and are adjusting their holdings based on the level of investor sentiment.

There is body of literature that looks at investor sentiment and liquidity. Baker and Stein (2004) propose that irrational investors will only participate in the market when they are optimistic and these irrational investors increase market liquidity. Their proposal suggests that the market should be more liquid following high sentiment than low sentiment. Consistent with this proposal, the existing literature has found a negative relation between investor sentiment and liquidity (see for example Chen et al. (2009), Deuskar (2008), and Lin (2011)). I find supporting evidence of a negative relation between investor sentiment and liquidity. However, unlike the existing literature which focuses on the market as whole, my results show that the liquidity of profitable trading strategies is affected by investor sentiment. Additionally, to my knowledge I am the first to test whether the higher returns experienced by some trading strategies following different sentiment states are due to trading frictions. For a collection of 16 trading strategies, I generally find that these strategies are more illiquid following low sentiment than high sentiment. Further, I also find that the majority of the short leg portfolios of each trading strategy to be more illiquid than the long leg portfolios. These results are robust even when I expand the number trading strategies to an additional 34 trading strategies.

My work is related to 3 recent papers in the finance literature. Chordia et al. (2014) look at whether the profits to 12 trading strategies have decreased over time. They suggest that since liquidity in the market has improved over time, arbitrageurs should be able to reduce the profits to the 12 trading strategies. They find evidence consistent with their suggestion. The profits to these strategies in recent times are lower than they were in prior periods. My work is also related Hwang and Liu (2014). Hwang and Liu investigate whether short sellers trade on 10 profitable trading strategies that were previously reported in the literature. They find that the short interest of securities in the short leg increases after those securities are classified as being in the short leg, so they conclude that short sellers must be trading on those strategies. Finally, my work is related to Wu and Zhang

(2014). Wu and Zhang calculate the average illiquidity, institutional ownership, and short interest for a strategy that combines 19 different trading strategies into 1 strategy. They find for this 1 strategy institutional ownership is higher for the long leg than the short leg, short interest is higher for the short leg portfolio, and illiquidity is higher for the long leg than the short leg.

While my work shares some similarities with Chordia et al. (2014), Hwang and Liu (2014), and Wu and Zhang (2014) there are some differences. First, none of those papers investigated how liquidity and trading frictions change following different sentiment states. I present evidence that differences in trading frictions may be driving the return differences between high and low sentiment states. Furthermore, our results imply that financial institutions are altering their portfolios based on the level of sentiment and that the trades of financial institutions could be contributing to the higher return of the short leg portfolio following low sentiment. Unlike Wu and Zhang (2014), I find that illiquidity is generally higher for the short leg portfolio than the long leg portfolio. The reason that Wu and Zhang (2014) present a different result than us is most likely due to their methodology. They calculate illiquidity for a single composite strategy whereas I look at illiquidity for each strategy separately.

2.2 Data and Methodology

I consider a total of 50 long-short trading strategies. These trading strategies were used in Bulsiewicz (2013) to assess whether the returns to profitable trading strategies are due to short sale constraints. The full list of trading strategies considered in this paper is given in Appendix A. The data needed to allocate securities into the long leg and short leg of each trading strategy come from CRSP, COMPUSTAT, and I/B/E/S. The main investor sentiment index used in this paper is the Baker and Wurgler (2006) orthogonalized investor sentiment index. Data for this index are obtained directly from Jeffrey Wurgler's website. The University of Michigan consumer confidence index and additional data needed to construct the University of Michigan residual consumer confidence indices are obtained from the Federal Reserve Bank of St. Louis website.

In this paper I am interested in testing whether the average security in these strategies conforms to Miller's (1977) hypothesis, that is, is the average security in these strategies hard-to-short, and does it become overvalued following high sentiment? In order to test whether Miller's hypothesis holds, additional financial variables that measure liquidity, short sale constraints, and equity valuation are constructed. In order to construct these variables, data from CRSP, COMPUSTAT and I/B/E/S are augmented with short interest data from the COMPUSTAT Supplemental file and institutional ownership data from the Thompson Reuters 13F database.

2.2.1 Overview of Short Sale Constraint Measures

In the first part of this paper, I am interested in determining what fraction of the 50 trading strategies is invested in hard-to-short securities. To be able to assess whether or not each trading strategy is heavily invested in hard-to-short securities, I need to be able to determine whether or not a security is hard-to-short. I consider a security as having high short sale constraints if it has a low share price, is relatively illiquid, has low analyst coverage, has high transaction costs, etc. Initially, I consider a total of 32 different proxies for whether or not a security has high short sale constraints. The first 29 short sale constraint proxies cover such variables as share price, firm size, liquidity, profitability, analyst coverage and forecast dispersion, volatility, idiosyncratic risk, short interest, transaction costs, and relative valuation. Similar in methodology to Stambaugh et al. (2012a), I also construct 3 composite measures that combine the information in the 29 unique short sale constraint proxies. The 29 measures of whether a security has high short sale constraints have either been shown to be correlated with short sale loan fees or proxy for securities that are likely costly to arbitrage (see for example D'Avolio (2002), Diether and Werner (2011), Mashruwala et al. (2006), Kumar and Lee (2006), Lam and Wei (2011), and Boehmer et al. (2010)). A more detailed description of all 32 trading friction measures is given in Appendix B.

Following the methodology previously used in Bulsiewicz (2013), I sort firms in June of year *t* on 1 of the short sale constraint measures and allocate securities to 10 decile portfolios. I then calculate equally-weighted and value-weighted returns for the decile portfolio that is hardest-to-short, easiest-to-short, and easiest-minus-hardest to short portfolios from July of year *t* until June of year *t+1*. I also calculate a combination strategy that invests equally in all 32 different short sale constraints strategies. Next, I calculate the correlation matrix between the value-weighted lowest minus highest trading friction portfolios and remove strategies that have a correlation greater than or equal to 0.80.

After removing highly correlated strategies, I am left with 16 trading strategies constructed using 1 of the 16 short sale constraint measures. I use these 16 strategies and their underlying variable values in order to determine whether or not profitable trading strategies are heavily invested in hard-to-short securities and to assess whether there is a relation between investor sentiment and hard-to-short securities. The 16 remaining variables used as proxies for short sale constraints are: analyst coverage, average rank across all 32 hard-to-short proxies, book-to-market ratio, cash flow-to-average assets, Corwin-Schultz (2012) bid-ask spread, days-to-cover ratio, dollar short interest, forecast dispersion, institutional ownership, liquidity beta, momentum, share turnover, short interest, short-term reversal (current 1-month return and lagged 1-month return), and volatility.

I also supplement the 16 hard-to-short proxies with some additional financial proxies. D'Avolio (2002) suggests that illiquid securities have higher short sale constraints than other securities. To fully test whether the average security in the 50 strategies is illiquid, a total of 7 illiquidity measures are considered in this paper. These measures are Amihud's (2002) average 1-month daily illiquidity, 1-month percentage of zero trading days, Corwin-Schultz (2012) bid-ask spread, 1-month average daily dollar volume, share turnover, and trading volume, and Pastor and Stambaugh (2003) liquidity beta. Lesmond, Ogden, and Trczinka (1999) argue that investors will only trade a security if the expected return is greater than the trading costs. Thus, if a security is not traded on a given day then this could indicate that the security has high transaction costs. The Corwin-Schultz bid-ask spread measure is used because Corwin and Schultz (2012) provide evidence that their measure is just as good if not better than other low-frequency estimators.

Miller (1977) hypothesizes that heterogeneity in beliefs can lead to overvaluation. I directly test whether there is higher dispersion in beliefs following high sentiment using 2 measures: 1-month average return variance, and analysts' forecast dispersion. I also assess whether the average security in these strategies is hard-to-short using 3 additional measures: idiosyncratic risk, institutional ownership, and short interest. Shleifer and Vishny (1997) and Pontiff (2006) present an argument that securities with high idiosyncratic risk are harder-to-arbitrage than securities with low idiosyncratic risk since arbitrageurs are typically specialized investors who do not hold diversified portfolios. Therefore, securities with high idiosyncratic risk should be harder-to-short than securities with low idiosyncratic risk. Institutional ownership is used to measure short sale constraints since D'Avolio (2002) shows that securities with low institutional ownership or high short interest typically have higher short sale constraints, i.e., higher short sale loan fees.

2.2.2 Overview of Valuation Measures

I am also interested in finding out whether or not the average security in these trading strategies becomes overvalued (relative to the average valuation in the market) following high sentiment. To assess the overvaluation hypothesis, 7 measures of potential overvaluation are used: analysts' expected return, average recommendation, book-to-market ratio, and 4 measures of intrinsic value to market equity ratios. Analysts' expected 1-year return are used because if securities become overvalued following high sentiment then the average analyst should expect for these securities to earn a low return. Analysts' expected returns are constructed using their 1-year ahead price targets and the current value of equity in the market. If securities are more overvalued following high sentiment than low sentiment, then we would expect for analysts to be more likely to make a sell recommendation following high sentiment than following low sentiment. Additionally, if the average security in these strategies becomes overvalued then these securities should trade on a lower book-to-market ratio following high sentiment. Previously, Brav and Lehavy (2003) showed that analysts' target prices contain value-relevant information, i.e., the market reacts to price target revisions.

The final valuation measures are constructed using the ratio of intrinsic value to market value of equity. Frankel and Lee (1998) provide evidence that the ratio of intrinsic value to market value of equity is a good predictor of the cross-section of returns. Intrinsic value is calculated using Ohlson's (1995) residual income model. A total of 4 different measures of intrinsic value are used in this paper. For each of these measures intrinsic value is calculated using 7 different estimates of cost of capital: firm-level and industry-level cost of capitals estimated using the Fama and French (1993) 3-factor and Carhart (1997) 4-factor models, and constant costs of capital of 8%, 10%, and 12%. After calculating intrinsic value using each of these costs of capital, I then use the median intrinsic value from these formulas. If the intrinsic value is negative, then I set these values to missing. The first intrinsic value is calculated assuming that the firm's current return-on-equity remains constant in perpetuity. The other intrinsic values are calculated using analysts' mean annual earnings forecasts. The first measure calculates intrinsic value using 1-year ahead forecasts and assumes that the firm's expected 1-year ahead profitability will continue in perpetuity. The second measure uses 1-year and 2-year ahead mean earnings forecasts and assumes that the firm's profitability in year 2 will continue in perpetuity. The final measure of intrinsic value takes the median intrinsic value using the 14 estimates of intrinsic value calculated using I/B/E/S 1-year and 2-year forecasts. More details on the construction of each short sale constraints and valuation measures are presented in Appendix B.

2.2.3 Portfolio Formation Methodology

Following Bulsiewicz (2013), at the time of portfolio formation I use only common shares (share codes equal to 10 or 11), and exclude financials (SIC codes 6000-6999), utilities (SIC codes 4900-4999), and securities with share prices less than $5 or greater than

$1,000. Each trading strategy is formed in June of year *t* by sorting firms on a financial variable into decile portfolios. Then, from July of year *t* until June of year *t+1* equally-weighted and value-weighted portfolio values are calculated for each of the short sale constraint and valuation variables. I then estimate the average value of each short sale constraint and valuation variable following high and low sentiment by regressing trading strategy portfolio values on dummy variables indicating whether the prior period had high or low sentiment. Following Stambaugh, Yu, and Yuan (2012b), I define high investor as a month where the Baker and Wurgler (2006) orthogonalized investor sentiment index is above its median value for the entire sample period, 1965-2010. I also test for a predictive relation between the trading strategy short sale constraints and investor sentiment by regressing each time series on lagged investor sentiment. These steps are repeated for the remaining 49 trading strategies. After completing these steps, I then calculate the cross-section average long leg, short leg, and long-short variable values for each trading strategy in order to assess whether the average security in these strategies is hard-to-short and if these securities become overvalued following high sentiment.

2.3 Results

First, I investigate to what extent each trading strategy invests in securities with high short sale constraints. For each trading strategy, firms are sorted on 1 of the financial variables and assigned to a decile portfolio, with 1 extreme decile portfolio defined as the long leg and the other as the short leg. Independent of the trading strategy portfolio assignment, I allocate firms to 10 trading friction portfolios using 1 of the 16 trading friction measures. Next, each June, I calculate how much of the long leg and short leg portfolios are invested in securities assigned to the highest short sale constraints decile. For the combination trading strategy that was constructed by equally-weighting the first 11 trading strategies, each month I calculate the average weight invested in the highest short sale constraint decile across all 11 single-sort strategies. For each of the long-short portfolios, I calculate the weight invested in high short sale constraint securities as the difference in weights between the long leg and short leg portfolios. For the long leg, short leg, and long-short portfolios I calculate the equally-weighted and value-weighted time-series average weight invested in firms assigned to the highest short sale constraint decile. Then, I regress the long leg, short leg, and long-short portfolio time series of weights on the lagged high and low sentiment indicator variables constructed using the Baker and Wurgler (2006) investor sentiment index. I repeat these steps for each trading strategy. Finally, I take the cross-sectional average weight invested in high short sale constraint securities across the 50 trading strategies. These steps are repeated for the 15 other hard-to-short measures and for the 5 other sentiment measures. For brevity, I only report the results using Baker and Wurgler (2006) orthogonalized investor sentiment, but I obtain similar results using the other sentiment measures.

2.3.1 Average Weight Invested in Hard-to-Short Securities

The average weight invested in hard-to-short securities across the 16 short sale constraint proxies is reported in Panel A of Table 2.1. This table also reports, in Panels B and C, the average weight invested in hard-to-short securities across high and low sentiment states for each of the shorts sale constraint measures. Finally, Panel D reports the average weight that the 50 strategies invest in the smallest market capitalization decile. Looking at the equally-weighted portfolio results presented in Panel A, we see that on average around 16–17% of the long leg portfolios is invested in highly constrained securities while around 20–22% of the short leg portfolios is invested in hard-to-short securities, thus in net the long-short portfolios sell around 4–5% more hard-to-short securities than is purchased. Similar results are found when I look at value-weighted portfolios, although the average weights are now lower, approximately 10% of the long leg portfolios and 14% of the short leg portfolios is invested in highly constrained securities. So it does not appear that profitable trading strategies commonly reported in the literature take large positions in hard-to-short securities, and in particular, the short leg does not take a much larger position in hard-to-short securities than the long leg.

I also calculate the cross-sectional average weight invested in constrained securities following high and low sentiment for each of the 16 measures. These results are presented in Panels B and C of Table 2.1. Typically, the weight invested in constrained securities decreases when I switch from equally-weighted portfolios to value-weighted portfolios.

This is consistent with small firms having higher trading frictions than large firms.[7] This effect is particularly strong using the average rank measure. Using this measure, the weight invested in constrained securities decreases from 20% to 6% for the long leg portfolios and from 30% to 10% for the short leg portfolios. However, looking at dollar short interest we see that the average amount invested in highly constrained securities increases from around 4% of the long and short leg portfolios to around 33% and 25% for the long and short leg portfolios, respectively, when I switch from equally-weighted portfolios to value-weighted portfolios. This could be due to larger firms having relatively higher share prices than small firms and more shares outstanding than small firms (i.e., a

[7] Papers documenting that small firms have higher trading frictions than large firms include D’Avolio (2002), Lesmond et al. (1999), and Stoll and Whaley (1983) among others.

large firm and a small firm could have the same short interest ratio but since the large firm has more shares outstanding the dollar value of shares shorted is higher). In general, we once again see that the short leg invests only slightly more in highly constrained securities than the long leg and overall these positions are not large.

Previously Stambaugh et al. (2012b) found that there is a strong relation between the returns to a collection of 16 anomalies, but Bulsiewicz (2013) found that while some strategies are affected by investor sentiment, the returns to the majority of strategies have only a weak relation with investor sentiment. I investigate whether or not the reason that Bulsiewicz (2013) finds a different result than Stambaugh et al. (2012b) could be due to Bulsiewicz (2013) selecting trading strategies that take much smaller positions in hard-to-short securities. In unreported results, I find that the difference in average weights between the original strategies used in Stambaugh et al. (2012b) and the additional strategies used in Bulsiewicz (2013) is not statistically significant, suggesting that the weak relation between investor sentiment and profitable trading strategies reported in Bulsiewicz (2013) is not due to 1 group of strategies taking larger positions in hard-to-short securities.

Overall, the previous results show that profitable trading strategies are not heavily invested in hard-to short securities. Still, it could be argued that while these measures capture certain aspects of whether a security is hard-to-short it might be better to use a measure that combines all of these measures into 1 composite measure. To address this concern, I use firm size as a proxy for the extent to which a security is hard-to-short. In general, smaller firms are thought to be harder-to-arbitrage than larger firms. For example, Lesmond et al. (1999) show that smaller firms have higher transaction costs than larger firms and D'Avolio (2002) provides evidence that the securities of small firms have higher short sale constraints than those of larger firms.

I test to what extent the 50 strategies invest in the smallest size decile. Panel D of Table 2.1 presents the average weight invested in small firms for the cross-sectional average across all 50 strategies. The results are somewhat surprising if we assume that the short leg of these strategies is hard-to-short. Overall, using equally-weighted portfolios, both the long leg and the short leg invest around 40% in the securities of small firms. Further, the difference in weights between the long leg and the short leg is not statistically different from 0. If I use value-weighted portfolios, the long leg invests on average 5% in small firms and the short leg invests on average 6% in small firms. If the securities in the long leg are supposed to be easy-to-short, while the securities in the short leg are supposed to be hard-to-short, then it is not clear why the short leg portfolios only invests around 1% more in small firms than the long leg portfolios. Thus, even using firm size as the proxy for short sale constraints, we still reach the conclusion that these strategies are not heavily invested in hard-to-short securities.

2.3.2 Cross-Sectional Average Liquidity

The following section presents the results on whether the average security in the 50 strategies is hard-to-short and if these securities become overvalued following high sentiment. To be brief, I only present the cross-sectional results for all 50 strategies in the forthcoming tables. Generally, similar results are found within subsamples of the trading strategies, but I will also highlight interesting results for individual trading strategies, as necessary.

First, I assess whether the short leg of each trading strategy is more illiquid than the long leg and if the short leg is more illiquid following low sentiment. Amihud and

Mendelson (1986) and Amihud (2002) present theory and empirical evidence that suggests that returns increase with illiquidity. If the average security in the short leg is more illiquid than the long leg this would support the view that the returns to these strategies are due to short sale constraints. However, if the average security is not illiquid an alternative explanation would be needed to explain why certain short leg portfolios earn a higher return following low sentiment. Table 2.2 shows the average high and low coefficient estimates for the 7 liquidity measures. The results for equally-weighted portfolios are presented in Panel A.1 while the value-weighted results are presented in Panel B.1.

2.3.2.1 Amihud Illiquidity Results

Turning first to the results for Amihud illiquidity, the average security in both the long leg and short leg portfolios is more illiquid following low sentiment. This result is found for both equally-weighted and value-weighted portfolios, although illiquidity decreases quite a bit when value-weighted portfolios are used. However, the results indicate that the average illiquidity of the short leg is not statistically different from the average illiquidity of the long leg. Thus, the evidence so far indicates that the short leg is not harder-to-short than the long leg. Perhaps unsurprisingly, out of the 50 trading strategies, the securities with the highest illiquidity is found to be small firms and firms with low analyst coverage, while the most liquid firms are large firms and firms with high analyst coverage.

2.3.2.2 Trading Volume, Dollar Volume, and Share Turnover Results

The prior results indicate that based on Amihud's (2002) measure, these trading strategies are more illiquid following low sentiment. Since the Amihud measure is constructed using the ratio of absolute daily returns and dollar volume, this result could be due to higher dollar trading volume following high investor sentiment. To test this hypothesis, I calculate the cross-sectional average daily dollar volume, trading volume, and share turnover. The results for these 3 variables are reported in Table 2.2, with dollar trading volume in thousands and dollar volume in millions of dollars. For equally-weighted portfolios, there is approximately $3 million more in trading volume following high sentiment than following low sentiment and slightly higher trading volume and share turnover. However, the difference between the long leg and short leg is not statistically different from one another. On the other hand, for value-weighted portfolios, there is between $45 million more in trading volume following high sentiment than low sentiment and higher share turnover and trading volume. The long leg portfolios have on average 1 million more shares traded following high sentiment than low sentiment and the short leg portfolios have on average 837,000 more shares traded following high sentiment than low sentiment. This time, share turnover is statistically higher for the short leg than for the long leg, implying that under this measure the short leg is more liquid than the long leg.

I also investigate which trading strategies have the highest dollar volume and which trading strategies have the lowest dollar volume. Consistent with the earlier results using Amihud (2002) illiquidity, I find that large firms and firms with high analyst coverage have more than $100 million in trading volume than small firms and firms with no analyst coverage. Interestingly, for the trading strategy using Ohlson's (1980) O-score, the long leg is significantly more liquid than the short leg. Using equally-weighted portfolios, the difference in daily volume is approximately 1 million shares higher, irrespective of sentiment state, and the average dollar volume is $42 million higher following high sentiment and $27 million higher follower low sentiment. Using value-weighted portfolios, the difference in trading volume between the long leg and short leg is approximately 10 million shares higher following high sentiment and 6.6 million shares higher following low sentiment and trading volume is $332 million higher following high sentiment and $205 million higher following low sentiment. While the results for the strategy trading on Ohlson's (1980) O-score indicate that the long leg is more liquid than the short leg, overall the results indicate that the average security in the short leg is not less liquid than the long leg. Thus, the short leg does not appear to be harder-to-short than the long leg.

2.3.2.3 Corwin-Schultz (2012) Bid-Ask Spread Results

I investigate whether the short leg has higher transaction costs using the Corwin-Schultz (2012) bid-ask spread measure. Previously, Corwin and Schultz (2012) showed that their measure is just as good, if not better, than other estimators, and their measure is highly correlated with effective bid-ask spreads. Turning to the results presented in Table 2.2, the long leg has approximately 0.12% lower transaction costs for equally-weighted strategies and about 0.06-0.07% lower transaction costs for value-weighted strategies. For a $10 security, this equates to the average security in the short leg having transaction costs that are 1.2 cents higher using equally-weighted portfolios and 0.6 cents higher using value-weighted portfolios than the average security in the long leg. Additionally, transaction costs for these strategies are at least halved using value-weighted portfolios instead of equally-weighted portfolios. These results indicate that an investor would have slightly higher transaction costs short selling a short leg security rather than a long leg security.

2.3.2.4 Percentage of Zero Trading Days Results

As a robustness check, I also measure illiquidity using the percentage of trading days within a month with no trades, as indicated by zero trading volume on those days. A less frequently traded security should be harder-to-short than an otherwise identical security. The results presented in Table 2.2, Panel A.1 indicate that the average security in the long leg portfolios has a slightly higher chance of not being traded: there is a 4.55% chance of the long leg security not being traded following high sentiment and a 5.17% chance of the long leg security not being traded following low sentiment, while for the short leg these percentages are 3.52% and 4.35%, respectively. Based on this result, the short leg securities are easier-to-short than the long leg securities. The percentage of zero trading days drops significantly for both the long leg and short leg portfolios after value-weighting each security. Now both the long leg and the short leg have less than a 1% chance of not being traded. Additionally, the difference between the long leg and short leg is not statistically significant indicating that the short leg is not harder-to-short than the long leg based on these measures.

2.3.3 Cross-Sectional Average Short Sale Constraints

I further assess whether the average security in these strategies is hard-to-short using 5 measures: average daily return variance, forecast dispersion, idiosyncratic risk, institutional ownership, and short interest. Based on Miller's (1977) argument, if the securities in the short leg have wider dispersion in beliefs following high sentiment then this could result in lower returns following high sentiment. Thus, Miller's argument would be able to explain the result found in Stambaugh, Yu, and Yuan (2012b), who found that the short leg portfolios of a set of 16 strategies have lower returns following high sentiment.

2.3.3.1 Average Daily Return Variance and Forecast Dispersion Results

I directly assess whether the 50 strategies have wider dispersion in beliefs following high sentiment using average daily return variance and analysts forecast dispersion. The cross-sectional average return variance and forecast dispersion for the 50 strategies are presented in Table 2.2, Panels A.2 and B.2. Both measures of dispersion in beliefs provide the same conclusion: the long leg and short leg have wider dispersion in beliefs following high sentiment, with the larger dispersion of beliefs residing in the short side of each strategy. Thus, this result provides some evidence that the short leg may have slightly higher short sale constraints than the long leg. Additionally, using value-weighted portfolios there is not a statistical or economic difference in forecast dispersion between high and low sentiment for the long leg portfolios but there is a statistical and economic difference for the short leg portfolios. In unreported results, I also find that there is not a statistical difference in beliefs dispersion for the 16 strategies used in Stambaugh, Yu, and Yuan (2012) and the 34 additional strategies used in Bulsiewicz (2013), which provides supporting evidence that the results presented in Bulsiewicz (2013) are not due to selecting strategies with homogeneous beliefs.

2.3.3.2 Idiosyncratic Risk Results

I also test if the short leg securities have high short sale constraints using idiosyncratic risk. If the short leg is harder-to-short than the long leg, then the short leg should have higher idiosyncratic risk. The average security in these strategies has higher idiosyncratic risk following high sentiment than low sentiment. Furthermore, using either equally-weighted or value-weighted portfolios, the average securities in the short leg has slightly higher idiosyncratic risk than the average security in the long leg. This difference in idiosyncratic risk is 0.35% following high sentiment and 0.22% following low sentiment, indicating that the short leg is marginally harder-to-short than the long leg.

2.3.3.3 Institutional Ownership Results

If the securities in the short leg of each strategy are hard-to-short, then they should have low institutional ownership. However, I find that the average security in the 50 strategies does not have low institutional ownership. Panel A.2 of Table 2.2 shows the cross-sectional average institutional ownership using equally-weighted portfolios and Panel B.2 of Table 2.2 shows the cross-sectional average institutional ownership using value-weighted portfolios. Regardless of the weighting scheme, the average security in these strategies does not appear to be hard-to-short. The average security in the long leg has institutional ownership above 38% and the average security in the short leg has institutional ownership above 35%.

Surprisingly, there is a large difference in institutional ownership between sentiment states. Using equally-weighted portfolios, both the long leg and short leg portfolios have institutional ownership that is more than 9 percentage points higher following low sentiment than following high sentiment. Furthermore, this effect remains using value-weighted portfolios. Using value-weighted portfolios, the average security in the long leg portfolios has institutional ownership that is close to 6.8 percentage points higher following low sentiment, while the average security in the short leg portfolios has institutional ownership that is more than 7.5 percentage points higher following low sentiment. These results suggest that these strategies are harder-to-short following high sentiment, but the average security in the long and short leg portfolios is not hard-to-short. Further, there is not a large difference in institutional ownership between the average security in the long leg and short leg portfolios.

2.3.3.4 Short Interest Results

D'Avolio (2002) presents evidence that securities with high short interest are harder-to-short than securities with low short interest. As a further robustness check, I use short interest as the proxy for short sale constraints. The average cross-sectional level of short interest across the 50 trading strategies is reported in Table 2.2. For both the long leg and short leg portfolios, I find that the average security has less than 2% of its shares outstanding that are sold short. This result is obtained using equally-weighted and value-weighted portfolios. Additionally, this evidence again shows that the average security in these strategies is not hard-to-short.

2.3.4 Institutional Ownership by Institution Type

Previously, evidence was presented indicating that financial institutions hold a larger portion of shares outstanding following low sentiment. The question then arises, are all financial institutions increasing their ownership stakes following low sentiment or are only a subsample of financial institutions increasing their ownership stakes? To investigate this issue, I calculate the percentage of shares outstanding held by 3 different types of financial institutions: banks, insurance companies, and other financial institutions. Financial institutions are classified using the classification codes provided by Thomson Reuters. Following the methodology of Lewellen (2011), financial institutions classified by Thomson Reuters as investment companies, investment advisors, or other are merged together into a single group. The Thomson Reuters' institution type code at the end of 1997 is used for any institution that is in the database after that date instead of updating it if the classification changes. Table 2.3 presents the cross-sectional average ownership for each of the 5 financial institution types.

2.3.4.1 Banks

First, I investigate whether banks increase their holdings following low investor sentiment. Based on the evidence presented in Table 2.3, banks do not drastically change their holdings based on the level of investor sentiment. For both the long leg and short leg portfolios, the difference in bank ownership between high and low sentiment states is on average less than 1 percentage point. Additionally, the difference in bank holdings between the long leg and short leg portfolios is on average less than 2.5 percentage points.

2.3.4.2 Insurance Companies

For insurance companies, the evidence presented in Table 2.3 indicates that these institutions maintain similar holdings across high and low sentiment states. Using equally-weighted portfolios, insurance ownership is around 2.3–2.90% of shares outstanding, and using value-weighted portfolios, insurance ownership is around 4.20–4.40% of shares outstanding. This suggests that insurance companies are passive investors, or at least, their net trades do not alter their overall level of ownership.

2.3.4.3 Other

The last category of financial institutions is all other institutions not belonging to the previous 2 categories. This category of financial institutions includes hedge funds, mutual funds, pension funds, and all other types of institutions except for banks and insurance companies. The results presented in Table 2.3 indicate that these institutions have much larger holdings following low sentiment than following high sentiment. For equally-weighted portfolios, their level of ownership is 8 to 9 percentage points higher following low sentiment, and for value-weighted portfolios, their level of ownership is around 7 percentage points higher following low sentiment. Additionally, these institutions have the largest amount of ownership relative to banks and insurance companies.

Overall, these results indicate that mutual funds, hedge funds, and other institutions are adjusting their holdings based on investor sentiment, while banks and insurance companies are not actively adjusting their holdings based on investor sentiment.

2.3.5 Overvaluation Results

Miller (1977) proposes that hard-to-short securities can become overvalued when investors are optimistic. I test whether this is the case for the 50 trading strategies. Specifically, I investigate whether the short leg becomes overvalued relative to the average valuation in the market. Using 7 different valuation measures, I present the cross-sectional average value of these variables across all trading strategies in Table 2.4.

2.3.5.1 Analysts' Expected Return Results

First, I assess whether the average security in these strategies becomes overvalued using analysts' expected return. Analyst expected return is defined as the difference between the mean 1 year ahead price target and the current market value of equity scaled by the current market value of equity. If the average security becomes overvalued, then analysts should expect a lower return following high sentiment than low sentiment. Additionally, if the average security in the short leg is hard-to-short then overvaluation should be strongest for the short leg securities. However, this is not what I find. Analysts have a higher expected return following high sentiment and they expect the short leg to earn a higher return than the long leg. Thus, this evidence is inconsistent with Miller's

(1977) framework. In unreported results, I find that this result is robust if the sample only uses those securities where more than one analyst provides a price target.

2.3.5.2 Average Recommendation

I check the prior results using analysts' average recommendation. If these strategies become overvalued following high sentiment then analysts should be less optimistic about these securities and give a higher recommendation, i.e., a sell recommendation. Since a recommendation of 1 is a strong buy, and a recommendation of 5 is a strong sell, the difference between the average recommendation following high sentiment and low sentiment should be positive. Consistent with the prior results, I find that, if anything, analysts think that the average security in these strategies is undervalued and not overvalued. The difference between the average recommendation following high sentiment and low sentiment is negative and found for both the long leg and the short leg. This again suggests that the average security in these strategies does not become overvalued following high sentiment.

2.3.5.3 Book-to-Market Ratio

I also test Miller's (1977) overvaluation hypothesis using the book-to-market ratio. If these strategies become overvalued following high sentiment, then the average security should have a lower book-to-market ratio following high sentiment than following low sentiment. Consistent with this reasoning, I find that both the long leg and the short leg have a lower book-to-market ratio following high sentiment than following low sentiment. On the other hand, the average security in the short leg does not appear to have a lower book-to-market ratio than the average security in the long leg. This result suggests that even though each strategy has a lower book-to-market ratio following high sentiment, the short leg does not become more overvalued relative to the long leg.

2.3.5.4 Compustat Intrinsic Value-to-Market Equity Ratio

Another measure that I use to test Miller's (1977) hypothesis is the ratio of intrinsic value-to-market value of equity. Intrinsic value is calculated using the residual income model. First, I calculate intrinsic value by assuming that each firm will maintain its current return on equity in perpetuity. I calculate the cost of equity using the Fama and French (1993) model, the Carhart (1997) model, or a constant cost of equity of either 8%, 10%, or 12%. After calculating the intrinsic value for each cost of equity, I then use the median value in calculating the ratio of intrinsic value to market equity. The median is used to control for extreme valuations. Additionally, this methodology is consistent with Miller (1997), who argues that hard-to-short securities should become overvalued relative to the average valuation in the market. Similar to the reasoning for book-to-market ratios, the average security in these strategies should have a lower intrinsic value to market equity ratio following high sentiment than following low sentiment. However, this is not what I find. The average security in the long leg and short leg portfolios has a higher intrinsic value to market equity ratio following high sentiment. This again suggests that these securities do not become overvalued following high sentiment.

2.3.5.5 I/B/E/S Intrinsic Value-to-Market Equity Ratio Results

To test the robustness of the prior results, intrinsic values are also calculated using 1-year ahead analysts' earnings forecasts or 1- and 2-year ahead analysts' earnings forecasts. In Table 2.4, the first measure is calculated using only 1-year ahead forecasts, the second measure is calculated using 1-year and 2-year ahead forecasts, and the third measure is calculated using the median value from both the first measure and the second measure. Inconsistent with Miller (1977), I again find little evidence of overvaluation. Using only 1-year ahead forecasts, the long and short leg portfolios have only slightly lower intrinsic value to equity ratios using equally-weighted portfolios. On the other hand, using value-weighted portfolios, the short leg has a lower intrinsic value to market equity ratio than the long leg following high sentiment. Thus, there is evidence with this measure of some overvaluation.

The previous results using only 1-year ahead forecasts presented some evidence of overvaluation for value-weighted portfolios. I test whether this result holds for the other measures calculated using analysts' 1-year and 2-year ahead annual earnings forecasts. Using 1-year and 2-year ahead forecasts, I find that both the average security in the long leg and short leg portfolios has a higher intrinsic value to market ratio following high sentiment. Additionally, the average valuation ratio for the short leg is either statistically indistinguishable from 0 or positive. Thus, using this measure the average security in the short leg is not overvalued relative to the average security in the long leg.

The final measure of intrinsic value uses the median value from both the intrinsic values calculated using only 1-year ahead forecasts and the intrinsic values calculated using 1-year and 2-year ahead forecasts. This measure is IBES intrinsic value-to-market equity ratio (3) in Table 2.4. Consistent with the results using 1-year and 2-year ahead forecasts, with this measure I again find that average security in these strategies does not become overvalued following high sentiment and the average security in the short leg does not become more overvalued than the average security in the long leg.

Overall, these results indicate that the average security in the short leg does not become overvalued relative to the average security in the long leg.

2.3.6 Market-Adjusted Short Sale Constraints Results

I investigate to what extent the average firm in these strategies is harder-to-short than the average firm in the market and if the average firm in these strategies becomes more overvalued than the average firm in the market. I calculate market-adjusted variable values each month by subtracting the cross-sectional equally-weighted average value of that variable from its un-adjusted value. The cross-sectional average values are calculated using all firms with share codes equal to 10 or 11. I then repeat the steps used in the previous section to calculate the cross-sectional average market-adjusted values across the 50 trading strategies for the short sale constraint variables and valuation variables.

2.3.6.1 Liquidity Results

The average market-adjusted liquidity across the 50 trading strategies is presented in Table 2.5, Panels A.1 and B.1. If the average firm in these strategies is more illiquid than the market, then the average market-adjusted Amihud (2002) illiquidity should be positive and statistically significant. Despite this prediction, this is not what is shown in Table 2.5. Both the long leg and short leg are more liquid than the average firm in the market following high sentiment and low sentiment. Additionally, the difference in liquidity between the average firm in these strategies and the market is largest following low sentiment than high sentiment, although from this test we cannot say whether this is due to the market being more illiquid, the average firm in these strategies being more illiquid, or a combination of the two.

Results similar to those found using Amihud's illiquidity measure are also found using the percentage of zero trading days and Corwin-Schultz's (2012) bid-ask spread measure. The average firm in the long and short leg portfolios has fewer zero trading days than the average firm in the market, with the average security in the short leg appearing to be slightly less liquid than the average security in the long leg. Using the Corwin-Schultz (2012) measure, the average firm in these strategies has lower transaction costs than the average firm in the market, with the short leg having marginally higher transaction costs than the long leg.

I also measure liquidity using market-adjusted daily trading volume, dollar trading volume, and share turnover. Using these measures, if the average firm in these strategies is harder-to-short than the market, then after controlling for the market, these measures should be negative on average. The evidence indicates that the average firm in these strategies is easier-to-short than the average firm in the market since the average market-adjusted daily volume, dollar trading volume, and share turnover are all greater than 0. Consistent with the results using unadjusted data, using market-adjusted trading volume and dollar trading volume, I find that the average security in the short leg is not harder-to-short than the average security in the long leg. Furthermore, using value-weighted portfolios, the average firm in the short leg has higher market-adjusted share turnover than the average firm in the long leg.

2.3.6.2 Belief Dispersion Results

Next, I assess whether the average firm in these strategies has higher belief dispersion than the average firm in the market. The results using market-adjusted average daily return variance indicate that the average firm in these strategies is not harder to short than the average firm in the market. Using either equally-weighted or value-weighted portfolios, both the long leg and the short leg have lower return variance than the average firm in the market. If belief dispersion is measured using market-adjusted forecast dispersion, a somewhat different result is obtained. Using equally-weighted portfolios, the average firm in these strategies has higher forecasts dispersion than the market, and the average security has higher forecast dispersion than the market following high sentiment than following low sentiment. This result changes when value-weighted portfolios are used. Now the average security in the long leg portfolios has lower forecast dispersion than the average security in the market while the average security in the short leg has forecast dispersion that is not statistically different from the average security in the market. This suggests that larger firms have lower forecast dispersion than smaller firms.

2.3.6.3 Institutional Ownership Results

Previously, Gompers and Metrick (2001) showed that institutional ownership has been increasing over time while Jiang (2010) controlled for this trend using market-adjusted institutional ownership. Thus, the results presented here should control for any bias imparted by the general increase in ownership over time. Consistent with the results using unadjusted institutional ownership, I find that the average firm in these strategies has institutional ownership that is higher than the average firm in the market. Additionally, once again, institutional ownership is higher following low sentiment than following high sentiment, although now the magnitude of this difference is not as large. Using equally-weighted portfolios institutional ownership is 3 to 4 percentage points higher following low sentiment, while using value-weighted portfolios institutional ownership is between 0.5 and 1.5 percentage points higher following low sentiment, thus a large portion of the difference in institutional ownership between high and low sentiment is due to the general increase in ownership over time. Overall, the results indicate that the average security in these strategies has higher institutional ownership than the average security in the market.

Therefore, the average security in these strategies is easier to short than the average security in the market.

2.3.6.4 Short Interest Results

I also use investigate whether the average security in the 50 strategies is hard-to-short using market-adjusted short interest. The results for this measure are presented in Table 2.5, Panels A.2 and B.2. Based on these results, the average security in these strategies is harder to short than the average security in the market, since the market-adjusted short interest is positive for the average securities in the long leg and short leg. On the other hand, there is a very small difference between market-adjusted short interest for the average security in the long leg and short leg portfolios, so the average security in the short leg is a little harder to short than the average security in the long leg.

2.3.6.5 Market-Adjusted Institutional Ownership by Type

Previously, the results indicated that banks and insurance companies are maintaining their holdings across sentiment states while other financial institutions are increasing their holdings following low sentiment. I test if this result remains after controlling for the average holdings of each institution type. Starting with banks, I calculated market-adjusted bank ownership each month by subtracting their cross-sectional average ownership from their raw ownership amount. Market-adjusted insurance ownership and market-adjusted other institutional ownership are calculated in a similar way. The results are presented in Table 2.6. Consistent with the results using unadjusted ownership, banks and insurance companies have similar ownership levels across sentiment states. Additionally, insurance companies have about the same holdings of securities in the long leg and short leg portfolios, while banks hold slightly higher ownership of the long leg portfolio than of the short leg portfolio. Even after controlling for the average level of ownership in the market, other financial institutions still hold a larger percentage of shares outstanding following low sentiment. For equally-weighted portfolios, the average market-adjusted ownership for other institutions is about 3 percentage points higher following low sentiment; for value-weighted portfolios, the average market-adjusted ownership is about 1.5–2.0 percentage points higher following low sentiment. This evidence again indicates that banks and insurance companies are passively managing their portfolios while other financial institutions are actively managing their portfolios.

2.3.7 Market-Adjusted Valuation Variable Results

Next, I investigate whether the average security in the 50 strategies becomes more overvalued than the average security in the market and if average security in the short leg becomes more overvalued than the average security in the long leg. The results for the 7 valuation measures are reported in Table 2.7.

2.3.7.1 Market-Adjusted Analysts' Expected Returns

The first measure of overvaluation is market-adjusted analysts' expected returns. If the average security in the 50 trading strategies becomes overvalued then the average market-adjusted expected return should be negative, and if the short leg becomes more overvalued than the long leg then the average security in the short leg should have a lower market-adjusted expected return than the average security in the long leg. I find some evidence that these strategies become overvalued. Using equally-weighted returns, the average market-adjusted expected return for the long leg is negative, although the difference between the expected return following high and low sentiment is not statistically different from 0. This suggests that the long leg does not become more overvalued following high sentiment. For the short leg portfolios, the average security has a higher expected return following high sentiment and the difference in expected returns between high and low sentiment is statistically positive (t=9.16). Contrary to Miller's (1977) hypothesis of overvaluation following optimistic periods, if anything, the short leg is undervalued following high sentiment.

Turning to the results for value-weighted portfolios, the long leg has lower market-adjusted return following high sentiment than following low sentiment suggesting that the long leg may become overvalued following high sentiment. On the other hand, the evidence once again indicates that the short leg if anything is undervalued following high sentiment.

2.3.7.2 Market-Adjusted Average Recommendations

I investigate Miller's (1977) overvaluation hypothesis using market-adjusted analysts' average recommendations. Since a strong buy is given a value of 1 and a strong sell is given a value of 5, if the average security in these strategies is overvalued relative to the market then the average market-adjusted analysts' recommendation should be positive. This is not what I find. For both the long leg and short leg portfolios, the average security has an average market-adjusted recommendation that is statistically greater than or equal to 0. Additionally, if the short leg becomes overvalued following high sentiment then the difference between the average market-adjusted recommendations between high and low sentiment should be positive. However, here the difference is statistically less than 0. This evidence again fails to support Miller's (1977) hypothesis.

2.3.7.3 Market-Adjusted Book-to-Market Ratio

If these trading strategies become more overvalued than the market, then the average security in these strategies should have a lower book-to-market ratio than the average security in the market. Thus, the average market-adjusted book-to-market ratio should be negative. Here, I do find evidence in favor of Miller's (1977) hypothesis. The average security in the long leg and short leg portfolio has a negative market-adjusted book-to-market ratio. This indicates that the average security in these strategies could be overvalued. However, upon closer inspection, the average security in these strategies appears to be more overvalued following low sentiment than following high sentiment, since the difference between market-adjusted book-to-market ratios between high and low sentiment is positive. This suggests that these strategies are undervalued following high sentiment. Additionally, all of the long-short coefficients are not statistically significant, implying that the short leg is not more overvalued than the long leg.

2.3.7.4 Market-Adjusted Compustat Intrinsic Value-to-Market Equity Ratio

Miller's (1977) overvaluation hypothesis is tested using market-adjusted intrinsic value to market equity ratios constructed assuming each firm's current profitability persists in perpetuity. The evidence here indicates that the average security in the long leg and short leg portfolios becomes more overvalued following high sentiment. The average market-adjusted intrinsic value-to-market equity ratio is negative and highly significant. Furthermore, the difference between high and low sentiment is negative and statistically significant.

While there is evidence that these strategies become overvalued, there is weak evidence that the short leg becomes more overvalued than the long leg. If the short leg is more overvalued than the long leg, then the coefficients for the long-short portfolio should be statistically positive. This is not what I find. All of the long-short coefficients are statistically less than or equal to 0. Thus, if these strategies do become overvalued, the short leg does not become more overvalued than the long leg.

2.3.7.5 Market-Adjusted I/B/E/S Intrinsic Value-to-Market Equity Ratio

To further test the overvaluation hypothesis, I use intrinsic values constructed using I/B/E/S analysts' annual earnings forecasts. The first measure that I use is constructed using only analysts' 1-year ahead earnings forecasts. From Table 2.7, Panel A, there is some evidence that the average security in these strategies is overvalued. However, the difference between the long leg and the short leg is not statistically different from 0. For value-weighted portfolios, there is again evidence of overvaluation, and the long-short portfolio has a positive and significant high sentiment and high-low sentiment coefficients. This suggests that the short leg is overvalued relative to the long leg.

Consistent with the results found using only 1-year ahead forecasts, the results found using intrinsic values constructed using 1- and 2-year ahead forecasts indicate that the average security in these strategies is more overvalued than the average security in the market. However, now the difference between these ratios between the long leg and short leg portfolios is not statistically different from 0. Thus, the short leg is not more overvalued than the long leg. Very similar results are found using ratios constructed using the median intrinsic value calculated using only 1-year ahead forecasts and intrinsic values calculated using both 1-year and 2-year ahead forecasts.

Overall, the majority of the evidence indicates that while these strategies invest in securities that appear to become overvalued, the short leg does not become more overvalued than the long leg. Therefore, Miller's (1977) framework does not hold for these strategies.

2.3.8 Size-Adjusted Results

As a final robustness check, I calculate the cross-average values of the short sale constraint and valuation variables using size-adjusted variable values. Size-adjusted variable values are calculated each month by subtracting the equally-weighted cross-sectional average value from the raw variable value. The equally-weighted cross-sectional average value is calculated using only those firms that are in the same size decile. Size deciles are determined using all securities with share codes equal to 10 or 11. Table 2.8 shows the cross-sectional average results across the 50 trading strategies using size-adjusted variables.

2.3.8.1 Liquidity Results

Consistent with the results found using market-adjusted results, I find that the average security in these strategies is more liquid than securities of firms with similar size. First, using equally-weighted portfolios, the average security in the long leg and short leg securities is more liquid than firms of similar size, as measured using Amihud's (2002) illiquidity measure or the percentage of zero volume trading days. Additionally, the average security has lower trading costs and higher trading volume, dollar volume, and share turnover. Further, there is not a statistical difference in trading volume and dollar volume for the long-short portfolio. This implies that the short leg is not more illiquid than the long leg. However, I do find that the average security in the long leg has a higher Pastor and Stambaugh (2003) liquidity beta, while the short leg has a lower Pastor and Stambaugh (2003) liquidity beta. Thus, it seems that these strategies are taking a hedge position against changes in liquidity.

Turning to the value-weighted portfolio results, these strategies are only slightly more liquid than the market. The magnitude of the Amihud (2002) illiquidity, percentage of zero volume trading days, and Corwin-Schultz (2012) bid-ask spread measures are smaller in magnitude using value-weighted portfolios than when using equally-weighted portfolios. Alternatively, daily trading volume and dollar volume are larger in magnitude using value-weighted portfolios, while share turnover is of similar magnitude. Again, the average security in the long leg has a larger Pastor and Stambaugh (2003) liquidity beta than firms of similar size, whereas the average security in the short leg has a smaller Pastor and Stambaugh (2003) liquidity beta than firms of similar size. These results imply that the average firm in these strategies is more liquid than firms of similar size. Therefore, so far these strategies are easier to short than firms of similar size.

2.3.8.2 Additional Short Sale Constraint Measures

I also assess whether the average security in these strategies have wider dispersion in beliefs and are hard-to-short relative to those securities of firms with similar market capitalization. The results for average return variance, forecast dispersion, idiosyncratic risk, institutional ownership, and short interest are presented in Panels A.2 and B.2 of Table 2.8. The results for equally-weighted portfolios are presented in Panel A.2 of Table 2.8. Mixed results are found for whether these strategies have wider beliefs dispersion. Looking at the results for average return variance, the average security in these strategies has lower average return variance than firms of similar size. However, the average security has wider forecast dispersion. Further, here the short leg appears to be harder-to-short than the long leg since average return variance and forecast dispersion are more positive.

Table 2.8 also shows the results for whether the average security in these strategies is harder to short than the securities of firms of similar size. The long leg and short leg have about the same idiosyncratic risk as firms of similar size, given that idiosyncratic risk is measured in percentages. In addition, looking at the results for institutional ownership both the long leg and the short leg have institutional ownership that is higher than securities of similar size, suggesting that these securities are easier to short than securities of similar size. However, the results using short interest indicate that the average security in these strategies has more or less the same short interest as the average security of similar size.

The results using value-weighted are somewhat different from the results using equally-weighted portfolios. The average security in these strategies has higher dispersion in beliefs as measured using average return variance and forecast dispersion. Further, the average security in the short leg has higher dispersion in beliefs than the average security in the long leg after controlling for firm size. Once again, idiosyncratic risk for these strategies is only moderately higher than the idiosyncratic risk for securities of similar size. Finally, the results for institutional ownership and short interest suggest that the average security in these strategies is a little harder to short than the security of similarly sized firms.

2.3.8.3 Size-Adjusted Institutional Ownership by Type

Next, I investigate if the results found for banks, insurance companies, and other institutions holds using size-adjusted ownership. Size-adjusted bank ownership is calculated for each security by subtracting the average level of bank ownership of securities in the same size decile from the raw level of bank ownership. A similar calculation is done to calculate size-adjusted insurance ownership and size-adjusted other institutional ownership. The average level of size-adjusted ownership for equally-weighted and value-weighted portfolios is presented in Table 2.9. For equally-weighted portfolios, the average size-adjusted bank and insurance ownership levels is fairly close to 0 implying that banks and insurance companies do not overweight the long leg and short legs of these strategies relative to the average security of similar size. Alternatively, other financial institutions hold more of these strategies than of securities of similarly sized firms. Additionally, there is still evidence that other financial institutions increase their holdings following low sentiment while the level of bank and insurance ownership is similar between sentiment states. Turning to the value-weighted portfolio results, these results are similar to the results found using equally-weighted portfolios. One difference is that other financial institutions have size-adjusted ownership that is closer to their ownership of the average security of firms with similar size.

<u>2.3.8.4 Size-Adjusted Valuation Results</u>

The results presented in Table 2.10 assess whether the average security in these strategies is more overvalued than the average security of similarly sized firms, and if the short leg becomes more overvalued than the long leg. The results for equally-weighted portfolios are presented in Panel A. Consistent with the results using raw and market-adjusted analysts' expected returns, once again the average security in the short leg has a higher expected return than the average security in the long leg. Further, the average security in the short leg has a higher expected return than the average security of similar size, while the average security in the long leg has a lower return than the average security of similar size. Even further, the average security in the short leg has a higher size-adjusted expected return following high sentiment than following low sentiment. This suggests that the short leg is undervalued rather than overvalued.

The results for size-adjusted analysts' recommendations present a similar result. If the securities in the short leg are more overvalued than the securities of firms of similar size, then the average size-adjusted recommendation should be positive. However, this is not what the results in Table 2.10 indicate. The average security in the short leg has a size-adjusted recommendation that is statistically negative, there is not a statistical difference between high and low sentiment, and there is not a statistical difference between the long leg and short leg. Thus, the average security in the short leg is not viewed to be more overvalued than the average security in the long leg.

For the book-to-market ratios and intrinsic value-to-market equity ratios, if the short leg is more overvalued than the long leg then the average security in the short leg should have a negative size-adjusted valuation ratio, and the long-short portfolio should have a positive average size-adjusted valuation ratio following high sentiment as well as a positive high-low average size-adjusted valuation ratio. The results indicate that the short leg has a negative size-adjusted book-to-market ratio, indicating a higher valuation than the average firm in the same size decile. On the other hand, the long-short portfolio does not have an average size-adjusted book-to-market that is statistically different from 0. Thus, the null of no overvaluation cannot be rejected. A fairly similar result is found using the valuation ratios constructed using intrinsic values. All of the results for these measures indicate that the average security in the short leg is more overvalued than the average security of similar size. For 3 of the measures there is no evidence that the short leg is more overvalued than the long leg. However, using intrinsic values constructed using only 1-year ahead earnings forecasts, the short leg appears to be slightly more overvalued than the long leg; the average intrinsic value-to-market equity ratio is 0.06 following high sentiment, 0.0212 following low sentiment, resulting in a high-low sentiment average difference of 0.0387.

Turning to the value-weighted portfolio results, again there is evidence that the short leg is undervalued relative to the long leg using analysts' expected returns and analysts' average recommendation. The intrinsic value-to-market equity ratio constructed using only 1-year ahead forecasts indicate that the short leg may be marginally more overvalued than the long leg. However, there is no evidence that the short leg is more overvalued than the long leg using size-adjusted book to market ratios and intrinsic value-to-market ratios constructed using 1-year and 2-year ahead earnings forecasts or the median intrinsic value constructed using 1-year or 1- and 2-year ahead earnings forecasts.

2.3.9 Difference in Means Test

The previously reported results used the full sample of 50 trading strategies to test if the average security conforms to Miller's hypothesis. There could be a concern that these results could be driven by the 34 additional trading strategies that were not used in Stambaugh, Yu, and Yuan (2012b). In this section I address this concern. For each short sale constraint, valuation and institutional ownership variable, I calculate the difference in cross-sectional means between the original 16 trading strategies used in Stambaugh, Yu, and Yuan (2012b) and the 34 additional trading strategies considered in Bulsiewicz (2013). The results for each of these variables is reported in Table 2.11. For brevity, I only report the results for unadjusted variables. The results using market-adjusted and size-adjusted measures produce very similar results. From Table 2.11, we can see that by and large there is not a large difference between the average security in the original 16 trading strategies and the additional 34 trading strategies. Thus, the results reported here are not due to selecting 2 samples with different characteristics.

2.3.10 Investor Sentiment and Short Sale Constraints

One question that is not fully answered is whether or not there is a statistical relation between investor sentiment and the hard-to-short securities in the long, short, and long-short portfolios and if the easy-to-short minus hard-to-short portion of each of these portfolios is more profitable following high sentiment than low sentiment. Previously Stambaugh et al. (2012b) presented evidence that the returns to a collection of 16 strategies have a relation with investor sentiment but Bulsiewicz (2013) presented evidence of a weak relation for a large collection of additional strategies and for simulated trading strategies. It could be the case that if we increased the weight that each strategy put on hard-to-short securities, we would find a strong relation between these strategies and investor sentiment. To address this question I calculate the equally-weighted and value-weighted returns of the hardest-to-short and easiest-to-short quintile portions of the long leg, short leg, and long-short portfolio. I then test whether the average excess return for each of these portfolios is statistically different between high and low sentiment and if there is a predictive relation between lagged investor sentiment level and portfolio returns.

Based on theory provided in Stambaugh et al. (2012b), there should not be a statistical relation for easy-to-short firms, so for these portfolios I use a two-tailed *t*-test with a critical *t*-statistic of 1.96. There should be a negative relation between hard-to-short firms and investor sentiment, so for these portfolios I use a one-tailed *t*-test with a critical *t*-statistic of 1.65, and there should be a positive relation for the easy-to-short minus hard-to-short portfolios so for these portfolios I use a one-tailed *t*-test with a critical *t*-statistic of

1.65.

Table 2.12 presents the cross-sectional average percentage of statistically significant coefficients for the easy-to-short and hard-to-short portions of the long leg and short leg quintile portfolios. In Table 2.12, Panel A documents the average percentage of statistically significant high-low sentiment average return coefficients and Panel B documents the average percentage of statistically significant predictive regression coefficients. Consistent with the evidence presented in Bulsiewicz (2013), on average I only find a statistical relation for easy-to-short securities in less than 30% of the strategies tested. Sometimes I find a high number of statistically significant coefficients for the hard-to-short securities within the long and short leg prior to controlling for the Fama and French factors. However, once I control for the Fama and French (1993) factors, the number of statistically significant coefficients drops dramatically. For example, using the University of Michigan residual consumer confidence index constructed using economic levels, I find approximately 85% of the hard-to-short securities within the short leg have a negative relation with investor sentiment, but once I control for the Fama and French (1993) factors this percentage drops to 23%. Another interesting finding in Panels A and B of Table 2.12 is that I generally find a higher percentage of statistically significant coefficients for the short leg portfolios than the long leg portfolios even when I test the easy-to-short firms within the short leg of each trading strategy. These results seem to indicate that the higher return of the short leg firms is not due to those securities being hard-to-short.

The previous literature has argued that there should be a statistical relation between the easy-to-short minus hard-to-short portfolio and investor sentiment.[8] I find weak support for this assertion. From Panel A of Table 2.12, we can see that across all sentiment measures the average percentage of statistically significant easy-to-short minus hard-to-short portions of the long leg and short portfolios is less than 30% without controlling for the Fama and French factors, and is less than 20% after controlling for the Fama and French factors. Turning to Panel B, which presents the average percentage of statistically significant predictive regression coefficients across all 50 strategies, I find weak support for a predictive relation between investor sentiment and the easiest-to-short minus hardest-to-short portfolios, usually less than 30% without controlling for the Fama and French factors, and even weaker support after controlling for the Fama and French factors. We can also see that these results are robust across 6 different sentiment measures.

The previous results provide supporting evidence that there is not a strong statistical relation between investor sentiment and hard-to-short securities. Before, the results reported in Table 2.12 relied on sorting on a particular trading strategy and then testing for a relation between investor sentiment and portfolio returns. Now, following the same formation methodology used in Bulsiewicz (2013) and Stambaugh et al. (2012b), I form decile portfolios by sorting firms directly on 1 of the 16 hard-to-short proxies and calculating equally-weighted and value-weighted returns for the hardest-to-short and easiest-to-short decile portfolios as well as the hardest-to-short minus easiest-to-short trading strategy. I then test for a relation between these 16 strategies and investor sentiment. These results are presented in Table 2.13 with Panels A and B presenting the number and

[8] See Stambaugh et al. (2012b) for an outline of this argument.

percentage of statistically significant high-low sentiment average return coefficients and predictive regression coefficients, respectively.

Looking at the results in Panel A, I find some support for the hypothesis of a relation between investor sentiment and hard-to-short securities prior to controlling for the Fama and French (1993) factors, but once again, this relation becomes weaker after controlling for these factors. I find similar results when looking at the predictive regression results presented in Panel B. Still, there appears to be a weak relation between the hard-to-short minus easy-to-short portfolios and investor sentiment across the 6 sentiment measures used in constructing Table 2.13. The maximum number of statistically significant high-low average return coefficients for the hardest-to-short decile portfolio are found using Baker and Wurgler (2006) orthogonalized investor sentiment, 10 out of 16 (62.50%) are statistically significant after controlling for the Fama and French factors. On the other hand, using the other sentiment measures, on average less than 50% of the coefficients are statistically significant. Additionally, there is only weak support that the returns to each of the hard-to-short strategies are higher following high sentiment than low sentiment. In Panel B of Table 2.13 we can see that similar results are found when I test for a predictive relation between strategies that trade directly on hard-to-short measures and investor sentiment.

Overall, these results provide further evidence that the relation between investor sentiment and portfolio returns is not due to short sale constraints. The evidence indicates that the short legs of each of the 50 strategies do not take huge positions in hard-to-short securities. Additionally, when I directly test securities that are thought to be hard-to-short for a relation between their returns and investor sentiment, I only find weak to moderate support for the assertion that these securities have different payoffs in different sentiment states.

The prior analysis showed that while generally profitable trading strategies have a weak relation with investor sentiment, there are still some strategies that have a relation with investor sentiment. To further investigate whether this result is due to short sale constraints, I test how the prior results would change if hard-to-short securities are excluded at the time of formation of the 50 trading strategies. If the relation between the returns of some trading strategies and investor sentiment is due to short sale constraints, then we should see a large decrease in the number of statistically significant coefficients after excluding securities that are hard-to-short. For convenience, Table 2.14 shows the number of statistically significant high-low sentiment and predictive regression coefficients without excluding any firms based on short sale constraints, the results after excluding securities with high short sale constraints, and the results after excluding securities of small firms.

As a starting point, I assess how the relation between investor sentiment and trading strategy returns changes after excluding hard-to-short securities. For each of the 50 trading strategies, at the time of formation, firms are removed that are thought to be hard-to-short. To be conservative, this typically entails removing firms that are in the hardest-to-short quintile. The methodology for the majority of the hard-to-short proxies is as follows:

1. Sort firms on 1 of the 50 trading strategy variables into long leg and short leg portfolios
2. Independent of step #1, sort firms into quintile portfolios on 1 of the 16 hard-to-short variables

3. Based on the sort in step #2, if a security is in the hardest-to-short quintile then remove this firm from the long leg or short leg portfolios
4. Calculate equally-weighted and value-weighted returns for each strategy and run sentiment tests
5. Repeat steps #1–4 for the remaining hard-to-short proxies

The methodology is slightly different when excluding firms using analyst coverage, days-to-cover, dollar short interest, and short interest. Firms with no analyst coverage are excluded from the long leg and short leg portfolios. For days-to-cover, dollar short interest, and short interest securities with no shares sold, short are placed in 1 portfolio and 4 additional portfolios are formed using 25 percentile breakpoints. Then for these 3 hard-to-short proxies, securities above the 75^{th} percentile are excluded from the long leg and short leg portfolios.

The average percentage of statistically significant coefficients after excluding firms on each of the 16 hard-to-short proxies are reported in Table 2.14 with Panel A showing the average percentage of statistically significant high-low portfolio coefficients and Panel B showing the average percentage of statistically significant predictive regression coefficients. Compared to the results with no exclusions, the results after excluding hard-to-short firms are very similar. Take for example the equally-weighted portfolio results using the Baker and Wurgler (2006) orthogonalized investor sentiment index. Using this measure, prior to excluding firms, 86% of the 50 short leg portfolios had statistically significant high-low investor sentiment coefficients. After excluding firms, 80% of the coefficients were still statistically significant. Similarly, prior to excluding firms, 88% of the short leg predictive coefficients were statistically significant, and after excluding firms

72% of the coefficients remain statistically significant. Consistent results are found for the long leg and long-short portfolios. Further, this result is robust using the other 5 measures of investor sentiment. Thus far, the relation between investor sentiment and profitable trading strategies is fairly independent of whether or not hard-to-short securities are included in the portfolios.

To further test whether the relation between investor sentiment and profitable trading strategies is independent of short sale constraints, we repeat the prior analysis excluding firms in the lowest market capitalization quintile. D'Avolio (2002) presented evidence that small capitalization stocks are harder-to-short than large capitalization firms. However, D'Avolio also points out that most firms are not hard-to-short. By excluding the lowest quintile, this is removing hard-to-short securities as well as potentially some that might be easy-to-short. Therefore, this exclusion criterion is pretty conservative. The percentage of statistically significant high-low and predictive regression coefficients after excluding small firms is presented in Table 2.14. From this table we can once again see that even after removing firms that could be hard-to-short, we do not see a large change in the number of statistically significant coefficients. In fact, the percentage of significant coefficients only changes for 1 of the 6 sentiment proxies.

There could be a concern that the prior results are driven by a small subsample of the hard-to-short proxies. Therefore, in Table 2.15 I present the percentage of the 50 trading strategies with statistically significant coefficients for each of the 16 proxies. This table was constructed using the Baker and Wurgler (2006) orthogonalized investor sentiment index as the measure of investor sentiment. From this table, we see that, for the most part, there is not a lot of variation in the percentage of significant coefficients across the 16 short sale constraint proxies. For the majority of hard-to-short measures, the percentage of significant coefficients does not change greatly, even after excluding hard-to-short securities.

As a last robustness check, I vary the excluded percentile from 0% to 20% in increments of 1% and calculate the number of statistically significant coefficients after each iteration. Note an exclusion criterion of 0% implies that no firms are excluded. This is completed for 4 of the main proxies: average rank, firm size, institutional ownership, and short interest. Then for each proxy, the number of significant coefficients is plotted against the percentile cutoff. The number of significant coefficients using average rank, firm size, institutional ownership, and short interest are plotted in Figures 2.1–2.4. In the first column of each figure are the results for the long leg while the second and third column has the results for the short leg and long-short portfolios, respectively. In the first row are the number of statistically significant high-low coefficients without controlling for the Fama and French (1993) factors, the second row contains the high-low results after controlling for the Fama and French factors, and finally the third and fourth rows contain the number of statistically significant predictive regression coefficients prior to and after controlling for the Fama and French factors.

If the relation between investor sentiment and strategy returns is a result of short sale constraints, then we should see a sharp decline in the number of statistically significant coefficients as we change the exclusion criteria from 0% to 20%. This is not what we see in the figures. Instead of seeing a large drop in the number of statistically significant coefficients we see a gradual decline. For example, looking at the results for average rank, as the cutoff is increased, the number of significant short leg high-low coefficients in Panels (ii), (v), (vii), and (xi) decreases slowly. Furthermore, there are some plots where the number of statistically significant coefficients does not change at all, even after removing firms in the hardest-to-short quintile. It should be noted that since we are forming breakpoints independent of the trading strategy sort variable, often times we are removing more than the given percentile cutoff. Based on this evidence, it appears that the relation between investor sentiment and strategy returns is not due to overvaluation related to short sale constraints.

2.4 Conclusion

I test whether the average security across 50 trading strategies is hard-to-short and if it becomes overvalued following high sentiment. I find that the average security in these strategies is not hard-to-short. Furthermore, the average security in the short leg is not harder-to-short than the average security in the long leg. The average security in the short leg has fairly similar liquidity, institutional ownership, and short interest as the average security in the long leg. Additionally, while each trading strategy may be overvalued relative to the average valuation in the market, the short leg does not appear to be overvalued relative to the long leg. In fact, some evidence indicates that the short leg may be undervalued or, at a minimum, fairly valued.

The evidence also indicates that there may be an alternative explanation for why there is a relation between investor sentiment and a subsample of profitable trading strategies. I find that each trading strategy is more liquid following high sentiment and that institutional ownership is much higher following low sentiment. This suggests that the relation between investor sentiment and a subsample of profitable trading strategies could be due to illiquidity and institutional price pressure. Furthermore, I find that banks and insurance companies maintain their level of ownership across sentiment states, while other financial institutions such as mutual funds and hedge funds are increasing their holdings following low sentiment.

Overall, this evidence indicates that in general, profitable trading strategies do not conform to Miller's (1977) hypothesis of hard-to-short securities becoming overvalued following periods of optimism. Thus, more work is needed to disentangle the true cause of the relation between the returns of some trading strategies and investor sentiment.

Table 2.1

Average weight in hard-to-short and small securities. Each June, I sort firms on each trading strategy variable into 10 decile portfolios. Using each short sale constraint measure, and independent of the trading strategy sort, I sort firms on 1 of the short sale constraint measures and allocate firms to 10 decile portfolios. Then, for the long leg and short leg portfolio of each strategy, I calculate the equally- and value-weighted amount invested in the highest short sale constraint decile. I then calculate the time series average weight invested in high short sale constraint securities following high and low investor sentiment by regressing these weights on the lagged high and low sentiment indicators (constructed using the Baker and Wurgler (2006) orthogonalized investor sentiment index). Finally, for each short sale constraint proxy, I calculate the cross sectional average across all trading strategies considered. There are a total of 50 trading strategies considered. These strategies were previously used in Bulsiewicz (2013).

Panel A. Cross-sectional average weight in hard-to-short securities

		Long leg			Short leg			Long-Short		
Weighting Scheme	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Equally-weighted	Average weight	0.1701	0.1623	0.0079	0.2225	0.2036	0.0188	-0.0523	-0.0413	-0.0111
	t-statistic	(42.53)	(42.17)	(9.67)	(42.89)	(40.76)	(17.38)	(-8.96)	(-7.28)	(-9.87)
Value-weighted	Average weight	0.1063	0.1028	0.0036	0.1555	0.1392	0.0164	-0.0492	-0.0364	-0.0128
	t-statistic	(27.62)	(26.78)	(3.45)	(33.19)	(30.49)	(13.42)	(-8.39)	(-6.24)	(-7.63)

Panel B. Equally-weighted portfolios

Hard-to-short measure	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analyst coverage	Average weight	0.2416	0.2152	0.0263	0.2372	0.2058	0.0315	0.0043	0.0095	-0.0052
	t-statistic	(18.14)	(17.14)	(9.90)	(10.92)	(9.83)	(10.22)	(0.15)	(0.34)	(-1.12)
Average rank	Average weight	0.2022	0.2146	-0.0124	0.2932	0.3037	-0.0105	-0.0910	-0.0891	-0.0019
	t-statistic	(15.60)	(15.09)	(-4.99)	(21.83)	(19.97)	(-3.75)	(-3.92)	(-3.47)	(-0.44)
Book-to-market ratio	Average weight	0.1751	0.1435	0.0316	0.2536	0.1944	0.0592	-0.0785	-0.0510	-0.0274
	t-statistic	(11.96)	(11.54)	(7.64)	(12.87)	(10.02)	(13.03)	(-2.65)	(-1.87)	(-3.91)
Cash flow-to-average assets	Average weight	0.1900	0.1756	0.0145	0.3722	0.3279	0.0443	-0.1822	-0.1521	-0.0301
	t-statistic	(13.09)	(13.72)	(4.87)	(17.46)	(14.90)	(9.63)	(-5.60)	(-4.76)	(-5.38)
Corwin-Schultz bid-ask spread	Average weight	0.2963	0.3201	-0.0239	0.3069	0.3276	-0.0207	-0.0106	-0.0070	-0.0036
	t-statistic	(24.85)	(24.92)	(-7.98)	(24.68)	(23.56)	(-5.74)	(-0.47)	(-0.29)	(-0.76)
Days to cover	Average weight	0.0579	0.0584	-0.0004	0.0671	0.0682	-0.0012	-0.0091	-0.0098	0.0007
	t-statistic	(32.76)	(37.45)	(-0.37)	(42.20)	(34.90)	(-0.86)	(-4.09)	(-4.42)	(0.40)
Dollar short interest	Average weight	0.0418	0.0412	0.0006	0.0319	0.0337	-0.0017	0.0099	0.0076	0.0023
	t-statistic	(5.14)	(5.33)	(0.49)	(3.36)	(3.79)	(-1.40)	(0.73)	(0.59)	(1.34)
Forecast dispersion	Average weight	0.1074	0.0989	0.0085	0.1513	0.1397	0.0116	-0.0439	-0.0408	-0.0031
	t-statistic	(17.71)	(16.57)	(7.20)	(7.91)	(7.28)	(8.53)	(-1.93)	(-1.80)	(-1.68)
Institutional ownership	Average weight	0.3500	0.3157	0.0342	0.3855	0.3450	0.0404	-0.0355	-0.0293	-0.0062
	t-statistic	(25.13)	(24.67)	(12.32)	(27.59)	(26.97)	(8.49)	(-1.45)	(-1.28)	(-1.07)
Liquidity beta	Average weight	0.1565	0.1542	0.0023	0.2442	0.2214	0.0228	-0.0876	-0.0671	-0.0206
	t-statistic	(20.06)	(21.03)	(0.82)	(12.16)	(11.11)	(8.73)	(-3.38)	(-2.64)	(-4.41)
Momentum	Average weight	0.1477	0.1234	0.0243	0.2506	0.2039	0.0467	-0.1029	-0.0805	-0.0225
	t-statistic	(11.09)	(10.37)	(9.98)	(11.54)	(9.60)	(14.06)	(-3.25)	(-2.71)	(-4.89)
Share turnover	Average weight	0.1870	0.1870	0.0000	0.2225	0.2123	0.0102	-0.0355	-0.0252	-0.0104
	t-statistic	(16.73)	(16.07)	(-0.01)	(27.51)	(24.56)	(4.16)	(-2.20)	(-1.50)	(-2.89)
Short interest	Average weight	0.0530	0.0562	-0.0031	0.0615	0.0670	-0.0055	-0.0085	-0.0108	0.0024
	t-statistic	(31.85)	(31.37)	(-3.54)	(26.97)	(24.79)	(-6.07)	(-2.81)	(-3.37)	(1.78)
Short-term reversal (1)	Average weight	0.1350	0.1292	0.0059	0.1985	0.1804	0.0181	-0.0635	-0.0511	-0.0123
	t-statistic	(21.12)	(22.48)	(3.01)	(10.85)	(9.93)	(7.17)	(-2.81)	(-2.32)	(-3.38)
Short-term reversal (2)	Average weight	0.1338	0.1331	0.0007	0.1998	0.1796	0.0202	-0.0660	-0.0465	-0.0195
	t-statistic	(23.88)	(22.64)	(0.32)	(21.73)	(18.96)	(8.22)	(-4.88)	(-3.40)	(-4.84)
Volatility	Average weight	0.2470	0.2304	0.0167	0.2838	0.2476	0.0362	-0.0368	-0.0171	-0.0197
	t-statistic	(15.31)	(15.07)	(6.03)	(29.91)	(27.24)	(13.85)	(-1.91)	(-0.93)	(-4.44)

Table 2.1 continued

Panel C. Value-weighted portfolios

Hard-to-short measure	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
Analyst coverage	Average weight	0.0352	0.0290	0.0062	0.0728	0.0583	0.0145	-0.0376	-0.0292	-0.0084
	t-statistic	(5.22)	(5.08)	(3.81)	(3.23)	(2.68)	(6.10)	(-1.53)	(-1.25)	(-2.89)
Average rank	Average weight	0.0499	0.0596	-0.0097	0.1010	0.1069	-0.0060	-0.0511	-0.0473	-0.0037
	t-statistic	(6.64)	(6.93)	(-4.97)	(10.85)	(9.87)	(-2.16)	(-3.51)	(-2.83)	(-1.07)
Book-to-market ratio	Average weight	0.2488	0.2451	0.0037	0.3061	0.2756	0.0305	-0.0572	-0.0307	-0.0266
	t-statistic	(11.22)	(10.04)	(0.56)	(13.36)	(11.77)	(4.33)	(-1.48)	(-0.75)	(-2.30)
Cash flow-to-average assets	Average weight	0.0834	0.0836	-0.0002	0.2327	0.2057	0.0269	-0.1493	-0.1220	-0.0273
	t-statistic	(9.22)	(9.81)	(-0.07)	(10.55)	(9.22)	(4.87)	(-5.29)	(-4.30)	(-4.07)
Corwin-Schultz bid-ask spread	Average weight	0.0690	0.0667	0.0023	0.0934	0.0922	0.0012	-0.0244	-0.0255	0.0011
	t-statistic	(7.71)	(6.79)	(1.05)	(10.47)	(9.22)	(0.32)	(-1.68)	(-1.56)	(0.23)
Days to cover	Average weight	0.0389	0.0515	-0.0127	0.0525	0.0622	-0.0098	-0.0136	-0.0108	-0.0028
	t-statistic	(21.78)	(18.66)	(-5.01)	(28.13)	(24.62)	(-3.63)	(-4.43)	(-3.04)	(-0.72)
Dollar short interest	Average weight	0.3328	0.3210	0.0117	0.2477	0.2547	-0.0069	0.0850	0.0664	0.0187
	t-statistic	(15.52)	(14.84)	(1.16)	(14.61)	(14.02)	(-0.73)	(2.47)	(1.85)	(1.21)
Forecast dispersion	Average weight	0.0840	0.0807	0.0033	0.1437	0.1307	0.0131	-0.0598	-0.0500	-0.0098
	t-statistic	(11.30)	(9.72)	(0.93)	(6.80)	(6.21)	(4.86)	(-2.39)	(-1.97)	(-2.15)
Institutional ownership	Average weight	0.0866	0.0921	-0.0054	0.1302	0.1237	0.0065	-0.0435	-0.0316	-0.0119
	t-statistic	(8.67)	(10.52)	(-1.98)	(10.01)	(11.17)	(1.50)	(-2.32)	(-1.96)	(-2.28)
Liquidity beta	Average weight	0.1035	0.0878	0.0156	0.2007	0.1556	0.0452	-0.0973	-0.0677	-0.0295
	t-statistic	(14.31)	(13.13)	(3.90)	(9.75)	(7.47)	(10.61)	(-3.84)	(-2.73)	(-4.29)
Momentum	Average weight	0.0839	0.0775	0.0064	0.1719	0.1378	0.0341	-0.0880	-0.0603	-0.0277
	t-statistic	(7.69)	(6.72)	(2.03)	(7.62)	(6.40)	(8.39)	(-3.03)	(-2.15)	(-5.39)
Share turnover	Average weight	0.1489	0.1445	0.0044	0.2164	0.1878	0.0287	-0.0676	-0.0432	-0.0243
	t-statistic	(12.24)	(11.21)	(1.45)	(20.71)	(18.10)	(9.28)	(-3.85)	(-2.41)	(-5.01)
Short interest	Average weight	0.0459	0.0516	-0.0056	0.0699	0.0666	0.0033	-0.0239	-0.0150	-0.0089
	t-statistic	(18.00)	(14.88)	(-3.26)	(23.59)	(19.51)	(1.75)	(-5.80)	(-3.02)	(-3.25)
Short-term reversal (1)	Average weight	0.0794	0.0696	0.0098	0.1389	0.1228	0.0162	-0.0596	-0.0531	-0.0064
	t-statistic	(13.68)	(12.86)	(4.65)	(7.22)	(6.36)	(7.24)	(-2.67)	(-2.42)	(-1.97)
Short-term reversal (2)	Average weight	0.0856	0.0691	0.0164	0.1447	0.1074	0.0373	-0.0591	-0.0382	-0.0209
	t-statistic	(16.04)	(13.73)	(5.95)	(15.63)	(12.67)	(12.96)	(-4.67)	(-3.22)	(-4.56)
Volatility	Average weight	0.1258	0.1151	0.0107	0.1663	0.1387	0.0276	-0.0405	-0.0236	-0.0169
	t-statistic	(9.54)	(9.37)	(3.13)	(18.58)	(15.37)	(9.82)	(-2.36)	(-1.48)	(-3.35)

Panel D. Average weight in smallest market capitalization quintile

Weighting Scheme	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
Equally-weighted	Average weight	0.4067	0.3892	0.0175	0.4175	0.3936	0.0238	-0.0108	-0.0041	-0.0067
	t-statistic	(18.63)	(18.26)	(5.30)	(24.21)	(22.13)	(7.08)	(-0.30)	(-0.11)	(-1.40)
Value-weighted	Average weight	0.0539	0.0533	0.0006	0.0635	0.0571	0.0064	-0.0096	-0.0038	-0.0058
	t-statistic	(2.75)	(2.72)	(0.65)	(6.60)	(6.49)	(2.63)	(-0.41)	(-0.16)	(-2.16)

Table 2.2

Cross-sectional average variable values following high and low sentiment. This table reports the cross-sectional average values for a collection of illiquidity and short sale constraint measures following high and low investor sentiment. Each June, I sort firms into 10 portfolios using 1 of the 50 trading strategy variables used in Bulsiewicz (2013). The extreme portfolio with firms that have the highest expected return is classified as the long leg while the other extreme portfolio is classified as the short leg. Starting with Amihud's illiquidity measure, I calculate the equally-weighted and value-weighted monthly average illiquidity for these 2 portfolios from July of year *t* until June of year *t+1*. Using these 2 time-series average portfolio illiquidity, I construct the long-short portfolio illiquidity as the difference between the monthly long leg and short leg portfolio illiquidity. I then calculate the average illiquidity, in percent form, following high and low investor sentiment by regressing the portfolio illiquidity series on the high and low sentiment indicator variable constructed using the Baker and Wurgler (2006) orthogonalized investor sentiment measure. I repeat these steps for the remaining 49 trading strategies. Using these estimates of illiquidity following high and low sentiment, I calculate the cross-sectional average illiquidity across all 50 trading strategies following high and low sentiment. This procedure is repeated for the remaining liquidity measures and for the additional short sale constraints measures. The results for Amihud's illiquidity, average percentage of zero trading days, Corwin-Schultz (2012) bid-ask spread, daily average dollar volume, share turnover, and trading volume, and Pastor and Stambaugh liquidity beta are presented in Panel A.1 and B.1. The results for the average return variance, forecast dispersion, idiosyncratic risk, institutional ownership, and short interest are presented in Panels A.2 and B.2. Panel A presents the results for equally-weighted portfolios and Panel B presents the results for value-weighted portfolios.

Panel A. Equally-weighted portfolios

Panel A.1 Liquidity related variables

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	0.7929	1.1468	-0.3539	0.9252	1.2256	-0.3005	-0.1324	-0.0790	-0.0534
Amihud illiquidity	*t*-statistic	(15.73)	(14.69)	(-11.76)	(15.47)	(17.21)	(-6.77)	(-1.35)	(-0.59)	(-0.92)
Average percentage of zero	Average	4.5513	5.1721	-0.6208	3.5210	4.3491	-0.8282	1.0318	0.8247	0.2071
trading days	*t*-statistic	(13.73)	(14.54)	(-11.10)	(12.02)	(13.12)	(-11.50)	(1.90)	(1.38)	(1.98)
	Average	0.6519	0.6656	-0.0137	0.7739	0.7560	0.0179	-0.1219	-0.0901	-0.0319
Corwin-Schultz bid-ask spread	*t*-statistic	(26.88)	(27.04)	(-2.58)	(27.77)	(24.28)	(2.56)	(-2.53)	(-1.74)	(-3.85)
	Average	15.5673	11.6657	3.9016	12.2210	9.0811	3.1399	3.3586	2.6185	0.7401
Daily dollar volume	*t*-statistic	(5.53)	(5.25)	(5.53)	(4.83)	(5.41)	(3.59)	(0.80)	(0.85)	(0.58)
	Average	0.5466	0.4739	0.0727	0.5957	0.5042	0.0914	-0.0489	-0.0296	-0.0192
Daily share turnover	*t*-statistic	(27.02)	(24.98)	(12.42)	(39.59)	(37.08)	(17.54)	(-1.65)	(-1.18)	(-2.67)
	Average	625.4004	603.9142	21.4863	528.8039	507.3530	21.4510	97.0192	98.1644	-1.1452
Daily volume	*t*-statistic	(6.08)	(5.78)	(1.59)	(6.36)	(7.50)	(1.25)	(0.66)	(0.71)	(-0.05)
Pastor-Stambaugh liquidity	Average	0.0330	0.0279	0.0052	-0.0447	-0.0293	-0.0155	0.0778	0.0570	0.0208
beta	*t*-statistic	(1.88)	(1.86)	(1.48)	(-2.51)	(-1.90)	(-4.20)	(2.20)	(1.88)	(3.13)

Panel A.2 Additional hard-to-short measures

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	13.0651	10.4470	2.6181	16.8361	12.5393	4.2968	-3.7696	-2.0874	-1.6822
Average return variance	*t*-statistic	(29.11)	(31.06)	(15.46)	(36.40)	(33.28)	(27.44)	(-5.08)	(-3.51)	(-6.39)
	Average	0.3898	0.3493	0.0405	0.4882	0.4186	0.0695	-0.0987	-0.0694	-0.0293
Forecast dispersion	*t*-statistic	(21.02)	(20.48)	(10.76)	(18.70)	(17.35)	(19.55)	(-2.45)	(-1.86)	(-4.84)
	Average	2.5256	2.3272	0.1984	2.8813	2.5596	0.3217	-0.3556	-0.2317	-0.1238
Idiosyncratic risk	*t*-statistic	(51.27)	(52.60)	(15.40)	(61.25)	(55.58)	(27.12)	(-4.55)	(-3.14)	(-6.04)
	Average	38.3148	47.7479	-9.4331	35.7292	45.8978	-10.1686	2.5855	1.8501	0.7355
Institutional ownership	*t*-statistic	(42.56)	(64.63)	(-34.39)	(46.22)	(63.59)	(-36.40)	(1.81)	(1.40)	(2.66)
	Average	1.3867	1.4530	-0.0663	1.4761	1.5854	-0.1093	-0.0894	-0.1324	0.0430
Short interest	*t*-statistic	(45.35)	(38.19)	(-3.98)	(35.31)	(32.60)	(-8.09)	(-1.74)	(-2.28)	(2.04)

Table 2.2 continued

Panel B. Value-weighted portfolios

Panel B.1 Liquidity related variables

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	0.1025	0.1760	-0.0736	0.1631	0.2134	-0.0503	-0.0607	-0.0376	-0.0232
Amihud illiquidity	*t*-statistic	(3.90)	(4.04)	(-4.12)	(5.18)	(8.11)	(-3.15)	(-1.36)	(-0.66)	(-0.93)
Average percentage of zero	Average	0.4828	0.7044	-0.2215	0.5959	0.9171	-0.3212	-0.1131	-0.2129	0.0998
trading days	*t*-statistic	(4.10)	(4.53)	(-5.44)	(4.35)	(4.48)	(-3.98)	(-0.57)	(-0.76)	(1.04)
	Average	0.2343	0.2210	0.0133	0.3038	0.2802	0.0236	-0.0695	-0.0593	-0.0103
Corwin-Schultz bid-ask spread	*t*-statistic	(13.76)	(12.37)	(4.10)	(17.42)	(14.38)	(6.67)	(-2.45)	(-1.93)	(-2.03)
	Average	152.0191	98.4329	53.5862	127.4880	82.1282	45.3597	24.6788	16.6936	7.9852
Daily dollar volume	*t*-statistic	(11.16)	(10.84)	(8.50)	(11.89)	(13.46)	(8.60)	(1.12)	(1.21)	(0.80)
	Average	0.5563	0.4486	0.1078	0.6560	0.5039	0.1521	-0.0995	-0.0549	-0.0446
Daily share turnover	*t*-statistic	(23.16)	(22.16)	(12.68)	(31.99)	(27.72)	(18.05)	(-2.93)	(-1.96)	(-3.97)
	Average	4796.5598	3758.9660	1037.5938	4205.8353	3368.2645	837.5708	594.1159	400.6275	193.4883
Daily volume	*t*-statistic	(11.62)	(12.06)	(6.90)	(13.57)	(14.95)	(6.22)	(0.94)	(0.84)	(0.90)
Pastor-Stambaugh liquidity	Average	0.0036	0.0094	-0.0058	-0.0675	-0.0376	-0.0299	0.0711	0.0469	0.0242
beta	*t*-statistic	(0.24)	(0.76)	(-1.38)	(-4.89)	(-3.13)	(-7.58)	(2.49)	(1.94)	(3.54)

Panel B.2 Additional hard-to-short measures

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	7.8982	5.5379	2.3603	10.9280	7.0580	3.8700	-3.0292	-1.5208	-1.5084
Average return variance	*t*-statistic	(20.76)	(18.81)	(15.84)	(26.33)	(22.54)	(26.94)	(-4.62)	(-2.97)	(-6.61)
	Average	0.2433	0.2376	0.0057	0.3707	0.3244	0.0463	-0.1279	-0.0869	-0.0410
Forecast dispersion	*t*-statistic	(14.96)	(12.36)	(0.85)	(12.86)	(11.45)	(8.39)	(-3.24)	(-2.11)	(-4.17)
	Average	1.8001	1.5807	0.2195	2.1523	1.8046	0.3476	-0.3521	-0.2243	-0.1278
Idiosyncratic risk	*t*-statistic	(37.55)	(33.24)	(17.00)	(46.26)	(40.17)	(28.36)	(-4.43)	(-2.85)	(-6.68)
	Average	51.7998	58.6385	-6.8387	49.9083	57.4319	-7.5236	1.8915	1.2066	0.6849
Institutional ownership	*t*-statistic	(86.02)	(105.04)	(-20.58)	(75.08)	(91.78)	(-25.51)	(2.01)	(1.50)	(1.59)
	Average	1.1669	1.2266	-0.0597	1.3790	1.3975	-0.0186	-0.2121	-0.1709	-0.0412
Short interest	*t*-statistic	(29.16)	(24.22)	(-3.32)	(31.25)	(27.68)	(-0.99)	(-3.78)	(-2.56)	(-1.64)

Table 2.3

Cross-sectional average ownership following high and low sentiment by institution type. This table presents the cross-sectional average ownership across 50 trading strategies by financial institution type. Following the methodology outlined in Table 2.2, starting with percentage of outstanding shares held by banks, I calculate the time-series equally-weighted and value-weighted portfolio bank ownership for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average bank ownership following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross sectional average bank ownership across all 50 trading strategies. These steps are repeated for insurance companies and other financial institutions. Ownership coefficients are reported as percentage of shares outstanding held by that particular institution type.

Panel B. Value-weighted portfolios

Type of Institution	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	13.7901	13.3973	0.3928	11.5390	11.6367	-0.0977	2.2511	1.7606	0.4905
	t-statistic	(38.44)	(42.14)	(3.57)	(32.34)	(34.74)	(-1.19)	(3.56)	(3.13)	(3.28)
Insurance Companies	Average	4.2723	4.2493	0.0230	4.3512	4.3491	0.0021	-0.0789	-0.0998	0.0209
	t-statistic	(59.80)	(70.23)	(0.77)	(26.80)	(28.30)	(0.06)	(-0.42)	(-0.58)	(0.42)
Other	Average	33.7310	40.9919	-7.2610	34.0134	41.4461	-7.4327	-0.2824	-0.4541	0.1717
	t-statistic	(77.41)	(74.67)	(-25.17)	(75.24)	(87.09)	(-31.25)	(-0.52)	(-0.67)	(0.53)

Panel A. Equally-weighted portfolios

Type of Institution	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	7.5374	8.2669	-0.7294	6.3681	7.3624	-0.9944	1.1694	0.9044	0.2650
	t-statistic	(25.41)	(32.26)	(-11.05)	(23.01)	(30.02)	(-17.86)	(2.39)	(2.07)	(2.94)
Insurance Companies	Average	2.5153	2.8336	-0.3183	2.3863	2.6647	-0.2784	0.1290	0.1689	-0.0399
	t-statistic	(27.28)	(35.14)	(-12.31)	(24.87)	(34.88)	(-10.18)	(0.84)	(1.30)	(-1.01)
Other	Average	28.2416	36.6474	-8.4058	26.9606	35.8707	-8.9100	1.2810	0.7768	0.5042
	t-statistic	(51.22)	(81.22)	(-39.12)	(54.51)	(73.82)	(-38.11)	(1.50)	(0.94)	(2.55)

Table 2.4

Cross-sectional average valuation following high and low sentiment. This table presents the cross-sectional average valuation across 50 trading strategies for a collection of valuation measures. Following the methodology outlined in Table 2.2, starting with analysts' expected returns, I calculate the time-series equally-weighted and value-weighted portfolio values for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average analysts' expected return following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross-sectional average analysts' expected return across all 50 trading strategies. These steps are repeated for the remaining valuation measures. Analysts' expected return is calculated as the difference between analysts' most recent annual price target minus the stock's current share price scaled by the stock's current share price.

Panel A. Equally-weighted portfolios

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
Analysts' expected return	Average	53.7601	40.0084	13.7517	81.1647	46.4815	34.6832	-27.5085	-6.4785	-21.0300
	t-statistic	(20.81)	(22.41)	(8.92)	(23.04)	(24.32)	(14.99)	(-5.35)	(-1.98)	(-6.55)
Average Recommendation	Average	2.1469	2.2447	-0.0978	2.1071	2.2172	-0.1101	0.0400	0.0275	0.0124
	t-statistic	(115.48)	(138.53)	(-21.72)	(129.32)	(143.51)	(-20.04)	(1.23)	(0.92)	(1.59)
Book-to-market ratio	Average	0.8096	0.9648	-0.1552	0.7587	0.9134	-0.1547	0.0504	0.0511	-0.0007
	t-statistic	(19.37)	(19.93)	(-14.82)	(32.19)	(30.85)	(-13.75)	(0.84)	(0.73)	(-0.04)
Compustat intrinsic value-to-market equity ratio	Average	0.9446	0.8607	0.0840	1.1114	0.8326	0.2788	-0.1668	0.0279	-0.1948
	t-statistic	(30.13)	(29.46)	(6.27)	(32.42)	(49.02)	(8.98)	(-3.53)	(0.68)	(-5.01)
IBES intrinsic value-to-market equity ratio (1)	Average	0.7682	0.7740	-0.0058	0.7497	0.7616	-0.0119	0.0179	0.0127	0.0052
	t-statistic	(55.55)	(57.17)	(-1.41)	(67.67)	(57.61)	(-1.81)	(0.84)	(0.56)	(0.60)
IBES intrinsic value-to-market equity ratio (2)	Average	0.9157	0.8958	0.0199	1.0493	0.9848	0.0645	-0.1345	-0.0889	-0.0456
	t-statistic	(55.45)	(61.95)	(2.58)	(38.84)	(40.58)	(4.44)	(-3.82)	(-2.81)	(-2.85)
IBES intrinsic value-to-market equity ratio (3)	Average	0.8699	0.8647	0.0052	0.9948	0.9415	0.0533	-0.1256	-0.0766	-0.0490
	t-statistic	(55.64)	(59.02)	(0.68)	(38.44)	(40.86)	(4.15)	(-3.77)	(-2.49)	(-3.33)

Panel B. Value-weighted portfolios

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
Analysts' expected return	Average	36.2035	25.9602	10.2433	53.3456	28.5453	24.8003	-17.1964	-2.5885	-14.6079
	t-statistic	(17.04)	(20.88)	(7.68)	(18.79)	(21.38)	(13.85)	(-4.25)	(-1.18)	(-5.92)
Average Recommendation	Average	2.1761	2.2883	-0.1122	2.1154	2.2419	-0.1266	0.0610	0.0463	0.0148
	t-statistic	(141.95)	(148.09)	(-23.34)	(120.63)	(129.69)	(-16.42)	(2.10)	(1.58)	(1.62)
Book-to-market ratio	Average	0.6371	0.7224	-0.0854	0.6388	0.7070	-0.0682	-0.0024	0.0159	-0.0183
	t-statistic	(17.19)	(15.64)	(-7.18)	(27.20)	(24.13)	(-5.88)	(-0.05)	(0.24)	(-0.95)
Compustat intrinsic value-to-market equity ratio	Average	0.7749	0.7604	0.0145	0.8115	0.7204	0.0912	-0.0365	0.0400	-0.0765
	t-statistic	(31.12)	(31.00)	(1.91)	(23.89)	(43.65)	(2.81)	(-0.84)	(1.07)	(-2.19)
IBES intrinsic value-to-market equity ratio (1)	Average	0.7664	0.7681	-0.0017	0.6862	0.7325	-0.0463	0.0801	0.0359	0.0442
	t-statistic	(54.37)	(51.99)	(-0.28)	(63.72)	(50.74)	(-6.34)	(3.81)	(1.44)	(4.16)
IBES intrinsic value-to-market equity ratio (2)	Average	0.8455	0.8244	0.0210	0.8530	0.8232	0.0298	-0.0080	0.0015	-0.0095
	t-statistic	(46.29)	(61.06)	(1.79)	(34.06)	(58.08)	(1.66)	(-0.23)	(0.07)	(-0.41)
IBES intrinsic value-to-market equity ratio (3)	Average	0.8144	0.7963	0.0180	0.8096	0.7844	0.0252	0.0046	0.0122	-0.0075
	t-statistic	(45.09)	(57.65)	(1.61)	(33.29)	(56.40)	(1.48)	(0.14)	(0.55)	(-0.34)

Table 2.5

Cross-sectional average market-adjusted variable values following high and low sentiment. This table reports the cross-sectional average values for a collection of illiquidity and short sale constraint measures following high and low investor sentiment. Each June, I sort firms into 10 portfolios using 1 of the 50 trading strategy variables used in Bulsiewicz (2013). The extreme portfolio with firms that have the highest expected return is classified as the long leg while the other extreme portfolio is classified as the short leg. Starting with Amihud's illiquidity measure, I calculate the equally-weighted and value-weighted monthly average illiquidity for these 2 portfolios from July of year *t* until June of year *t+1*. Using these 2 time-series average portfolio illiquidity, I construct the long-short portfolio illiquidity as the difference between the monthly long leg and short leg portfolio illiquidity. I then calculate the average illiquidity, in percent form, following high and low investor sentiment by regressing the portfolio illiquidity series on the high and low sentiment indicator variable constructed using the Baker and Wurgler (2006) orthogonalized investor sentiment measure. I repeat these steps for the remaining 49 trading strategies. Using these estimates of illiquidity following high and low sentiment, I calculate the cross-sectional average illiquidity across all 50 trading strategies following high and low sentiment. This procedure is repeated for the remaining liquidity measures and for the additional short sale constraints measures. The results for Amihud's illiquidity, average percentage of zero trading days, Corwin-Schultz (2012) bid-ask spread, daily average dollar volume, share turnover, and trading volume, and Pastor and Stambaugh (2003) liquidity beta are presented in Panel A.1 and B.1. The results for the average return variance, forecast dispersion, idiosyncratic risk, institutional ownership, and short interest are presented in Panels A.2 and B.2. Panel A presents the results for equally-weighted portfolios and Panel B presents the results for value-weighted portfolios.

Panel A. Equally-weighted portfolios

Panel A.1 Liquidity related variables

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	-2.2342	-3.9836	1.7493	-2.1029	-3.9021	1.7992	-0.1324	-0.0790	-0.0534
Amihud illiquidity	*t*-statistic	(-34.13)	(-41.83)	(52.50)	(-34.17)	(-54.03)	(48.72)	(-1.35)	(-0.59)	(-0.92)
Average percentage of zero	Average	-2.7860	-3.1011	0.3150	-3.8186	-3.9263	0.1077	1.0318	0.8247	0.2071
trading days	*t*-statistic	(-7.98)	(-8.26)	(5.52)	(-13.37)	(-12.01)	(1.44)	(1.90)	(1.38)	(1.98)
	Average	-0.5670	-0.8228	0.2558	-0.4455	-0.7339	0.2885	-0.1219	-0.0901	-0.0319
Corwin-Schultz bid-ask spread	*t*-statistic	(-18.78)	(-23.18)	(30.65)	(-18.17)	(-28.41)	(44.61)	(-2.53)	(-1.74)	(-3.85)
	Average	7.3444	5.4600	1.8844	3.9921	2.8597	1.1324	3.3586	2.6185	0.7401
Daily dollar volume	*t*-statistic	(2.68)	(2.58)	(2.64)	(1.57)	(1.68)	(1.30)	(0.80)	(0.85)	(0.58)
	Average	0.1185	0.1107	0.0077	0.1674	0.1405	0.0269	-0.0489	-0.0296	-0.0192
Daily share turnover	*t*-statistic	(6.28)	(6.95)	(1.73)	(10.91)	(10.58)	(6.84)	(-1.65)	(-1.18)	(-2.67)
	Average	280.8023	280.5458	0.2565	184.0063	183.2499	0.7564	97.0192	98.1644	-1.1452
Daily volume	*t*-statistic	(2.80)	(2.82)	(0.02)	(2.20)	(2.67)	(0.04)	(0.66)	(0.71)	(-0.05)
Pastor-Stambaugh liquidity	Average	0.0426	0.0257	0.0168	-0.0352	-0.0314	-0.0038	0.0778	0.0570	0.0208
beta	*t*-statistic	(2.42)	(1.71)	(4.84)	(-1.98)	(-2.04)	(-1.02)	(2.20)	(1.88)	(3.13)

Panel A.2 Additional hard-to-short measures

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	-7.5777	-10.0475	2.4698	-3.8092	-7.9735	4.1642	-3.7696	-2.0874	-1.6822
Average return variance	*t*-statistic	(-14.99)	(-19.78)	(11.10)	(-8.71)	(-20.86)	(20.87)	(-5.08)	(-3.51)	(-6.39)
	Average	0.0481	0.0279	0.0202	0.1466	0.0973	0.0494	-0.0987	-0.0694	-0.0293
Forecast dispersion	*t*-statistic	(2.59)	(1.63)	(5.37)	(5.63)	(4.04)	(13.84)	(-2.45)	(-1.86)	(-4.84)
	Average	-0.4131	-0.5114	0.0983	-0.0575	-0.2801	0.2226	-0.3556	-0.2317	-0.1238
Idiosyncratic risk	*t*-statistic	(-7.83)	(-9.97)	(6.84)	(-1.27)	(-6.43)	(19.11)	(-4.55)	(-3.14)	(-6.04)
	Average	8.8393	12.1697	-3.3304	6.2538	10.3196	-4.0659	2.5855	1.8501	0.7355
Institutional ownership	*t*-statistic	(10.80)	(16.47)	(-17.45)	(8.04)	(14.30)	(-20.38)	(1.81)	(1.40)	(2.66)
	Average	0.3965	0.4748	-0.0783	0.4859	0.6072	-0.1213	-0.0894	-0.1324	0.0430
Short interest	*t*-statistic	(14.13)	(15.01)	(-5.70)	(11.74)	(12.74)	(-9.59)	(-1.74)	(-2.28)	(2.04)

Table 2.5 continued

Panel B. Value-weighted portfolios

Panel B.1 Liquidity related variables

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
	Average	-2.9247	-4.9543	2.0296	-2.8649	-4.9143	2.0493	-0.0607	-0.0376	-0.0232
Amihud illiquidity	*t*-statistic	(-76.46)	(-86.61)	(92.58)	(-77.54)	(-123.43)	(153.19)	(-1.36)	(-0.66)	(-0.93)
Average percentage of zero	Average	-6.8545	-7.5688	0.7143	-6.7436	-7.3583	0.6147	-0.1131	-0.2129	0.0998
trading days	*t*-statistic	(-51.99)	(-44.58)	(17.03)	(-51.29)	(-36.06)	(7.19)	(-0.57)	(-0.76)	(1.04)
	Average	-0.9846	-1.2673	0.2828	-0.9156	-1.2098	0.2942	-0.0695	-0.0593	-0.0103
Corwin-Schultz bid-ask spread	*t*-statistic	(-44.57)	(-44.12)	(30.61)	(-58.00)	(-61.64)	(38.13)	(-2.45)	(-1.93)	(-2.03)
	Average	143.7962	92.2272	51.5690	119.2591	75.9068	43.3523	24.6788	16.6936	7.9852
Daily dollar volume	*t*-statistic	(10.59)	(10.26)	(8.18)	(11.08)	(12.34)	(8.24)	(1.12)	(1.21)	(0.80)
	Average	0.1282	0.0854	0.0428	0.2277	0.1402	0.0875	-0.0995	-0.0549	-0.0446
Daily share turnover	*t*-statistic	(5.33)	(4.34)	(5.65)	(11.09)	(8.25)	(12.61)	(-2.93)	(-1.96)	(-3.97)
	Average	4451.9616	3435.5975	1016.3641	3861.0377	3044.1615	816.8762	594.1159	400.6275	193.4883
Daily volume	*t*-statistic	(10.83)	(11.19)	(6.78)	(12.41)	(13.37)	(6.10)	(0.94)	(0.84)	(0.90)
Pastor-Stambaugh liquidity	Average	0.0131	0.0073	0.0059	-0.0580	-0.0398	-0.0182	0.0711	0.0469	0.0242
beta	*t*-statistic	(0.87)	(0.59)	(1.40)	(-4.20)	(-3.32)	(-4.59)	(2.49)	(1.94)	(3.54)

Panel B.2 Additional hard-to-short measures

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
	Average	-12.7446	-14.9566	2.2120	-9.7174	-13.4548	3.7374	-3.0292	-1.5208	-1.5084
Average return variance	*t*-statistic	(-28.82)	(-31.66)	(10.54)	(-24.61)	(-38.09)	(18.25)	(-4.62)	(-2.97)	(-6.61)
	Average	-0.0984	-0.0838	-0.0145	0.0291	0.0030	0.0261	-0.1279	-0.0869	-0.0410
Forecast dispersion	*t*-statistic	(-6.05)	(-4.36)	(-2.16)	(1.01)	(0.11)	(4.73)	(-3.24)	(-2.11)	(-4.17)
	Average	-1.1385	-1.2579	0.1194	-0.7865	-1.0351	0.2486	-0.3521	-0.2243	-0.1278
Idiosyncratic risk	*t*-statistic	(-22.10)	(-23.16)	(8.06)	(-17.57)	(-24.08)	(19.36)	(-4.43)	(-2.85)	(-6.68)
	Average	22.3244	23.0604	-0.7360	20.4328	21.8537	-1.4209	1.8915	1.2066	0.6849
Institutional ownership	*t*-statistic	(38.92)	(41.31)	(-2.61)	(29.46)	(34.93)	(-5.76)	(2.01)	(1.50)	(1.59)
	Average	0.1767	0.2484	-0.0717	0.3888	0.4193	-0.0305	-0.2121	-0.1709	-0.0412
Short interest	*t*-statistic	(4.28)	(4.86)	(-4.38)	(9.13)	(9.03)	(-1.81)	(-3.78)	(-2.56)	(-1.64)

Table 2.6

Cross-sectional average market-adjusted ownership following high and low sentiment by institution type. This table presents the cross-sectional average ownership across 50 trading strategies by financial institution type. Following the methodology outlined in Table 2.5, starting with percentage of outstanding shares held by banks, I calculate the time-series equally-weighted and value-weighted portfolio bank ownership for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average bank ownership following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross sectional average bank ownership across all 50 trading strategies. These steps are repeated for insurance companies and other financial institutions. Ownership coefficients are reported as percentage of shares outstanding held by that particular institution type.

Panel A. Equally-weighted portfolios

Type of		Long leg			Short leg			Long-Short		
Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	1.5548	1.9383	-0.3835	0.3855	1.0339	-0.6484	1.1694	0.9044	0.2650
	t-statistic	(5.28)	(7.56)	(-5.93)	(1.39)	(4.22)	(-11.89)	(2.39)	(2.07)	(2.94)
Insurance	Average	0.5259	0.7687	-0.2427	0.3969	0.5998	-0.2029	0.1290	0.1689	-0.0399
Companies	*t*-statistic	(5.80)	(9.53)	(-9.80)	(4.12)	(7.85)	(-7.52)	(0.84)	(1.30)	(-1.01)
Other	Average	6.7455	9.4628	-2.7172	5.4645	8.6860	-3.2215	1.2810	0.7768	0.5042
	t-statistic	(14.45)	(20.97)	(-21.28)	(11.06)	(17.88)	(-21.39)	(1.50)	(0.94)	(2.55)

Panel B. Value-weighted portfolios

Type of		Long leg			Short leg			Long-Short		
Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	7.6503	6.9723	0.6780	5.4580	5.2392	0.2188	2.1923	1.7331	0.4592
	t-statistic	(21.39)	(21.86)	(6.09)	(15.56)	(15.88)	(2.72)	(3.50)	(3.10)	(3.08)
Insurance	Average	2.2326	2.1507	0.0819	2.3100	2.2400	0.0700	-0.0773	-0.0893	0.0119
Companies	*t*-statistic	(31.61)	(36.05)	(2.75)	(14.77)	(15.51)	(2.09)	(-0.42)	(-0.55)	(0.24)
Other	Average	11.9351	13.5681	-1.6330	12.2554	14.0237	-1.7683	-0.3203	-0.4556	0.1353
	t-statistic	(29.55)	(25.52)	(-7.27)	(27.13)	(30.03)	(-9.77)	(-0.61)	(-0.69)	(0.43)

Table 2.7

Cross-sectional average market-adjusted valuation following high and low sentiment. This table presents the cross-sectional average valuation across 50 trading strategies for a collection of valuation measures. Following the methodology outlined in Table 2.5, starting with analysts' expected returns, I calculate the time-series equally-weighted and value-weighted portfolio values for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average analysts' expected return following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross-sectional average analysts' expected return across all 50 trading strategies. These steps are repeated for the remaining valuation measures. Analysts' expected return is calculated as the difference between analysts' most recent annual price target minus the stock's current share price scaled by the stock's current share price.

Panel A. Equally-weighted portfolios

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected	Average	-22.9051	-21.3287	-1.5765	5.0520	-14.8702	19.9222	-27.5085	-6.4785	-21.0300
return	*t*-statistic	(-8.87)	(-11.95)	(-1.02)	(1.51)	(-7.76)	(9.16)	(-5.35)	(-1.98)	(-6.55)
Average	Average	-0.0202	-0.0279	0.0077	-0.0601	-0.0554	-0.0047	0.0400	0.0275	0.0124
Recommendation	*t*-statistic	(-1.09)	(-1.72)	(1.70)	(-3.69)	(-3.58)	(-0.84)	(1.23)	(0.92)	(1.59)
	Average	-0.0809	-0.1155	0.0346	-0.1315	-0.1658	0.0343	0.0504	0.0511	-0.0007
Book-to-market ratio	*t*-statistic	(-1.95)	(-2.46)	(3.86)	(-5.47)	(-5.48)	(3.25)	(0.84)	(0.73)	(-0.04)
Compustat intrinsic	Average	-0.6240	-0.2470	-0.3770	-0.4578	-0.2751	-0.1827	-0.1668	0.0279	-0.1948
value-to-market	*t*-statistic	(-19.90)	(-8.45)	(-28.16)	(-13.40)	(-16.21)	(-5.88)	(-3.53)	(0.68)	(-5.01)
IBES intrinsic value-to-	Average	-0.2032	-0.1068	-0.0964	-0.2206	-0.1191	-0.1015	0.0179	0.0127	0.0052
market equity ratio (1)	*t*-statistic	(-14.69)	(-7.89)	(-23.46)	(-19.86)	(-8.99)	(-16.77)	(0.84)	(0.56)	(0.60)
IBES intrinsic value-to-	Average	-0.7071	-0.2394	-0.4677	-0.5638	-0.1510	-0.4127	-0.1345	-0.0889	-0.0456
market equity ratio (2)	*t*-statistic	(-42.82)	(-16.56)	(-60.73)	(-21.07)	(-6.21)	(-26.91)	(-3.82)	(-2.81)	(-2.85)
IBES intrinsic value-to-	Average	-0.7692	-0.2895	-0.4797	-0.6346	-0.2131	-0.4216	-0.1256	-0.0766	-0.0490
market equity ratio (3)	*t*-statistic	(-49.20)	(-19.76)	(-63.14)	(-24.53)	(-9.24)	(-32.21)	(-3.77)	(-2.49)	(-3.33)

Panel B. Value-weighted portfolios

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected	Average	-40.4617	-35.3769	-5.0848	-22.7671	-32.8064	10.0393	-17.1964	-2.5885	-14.6079
return	*t*-statistic	(-19.04)	(-28.46)	(-3.81)	(-8.36)	(-24.49)	(5.79)	(-4.25)	(-1.18)	(-5.92)
Average	Average	0.0090	0.0157	-0.0067	-0.0518	-0.0307	-0.0211	0.0610	0.0463	0.0148
Recommendation	*t*-statistic	(0.59)	(1.02)	(-1.39)	(-2.96)	(-1.77)	(-2.72)	(2.10)	(1.58)	(1.62)
	Average	-0.2535	-0.3579	0.1043	-0.2514	-0.3722	0.1208	-0.0024	0.0159	-0.0183
Book-to-market ratio	*t*-statistic	(-6.89)	(-7.87)	(9.01)	(-10.50)	(-12.17)	(10.12)	(-0.05)	(0.24)	(-0.95)
Compustat intrinsic	Average	-0.7938	-0.3473	-0.4466	-0.7577	-0.3873	-0.3703	-0.0365	0.0400	-0.0765
value-to-market	*t*-statistic	(-31.88)	(-14.16)	(-58.99)	(-22.43)	(-23.48)	(-11.43)	(-0.84)	(1.07)	(-2.19)
IBES intrinsic value-to-	Average	-0.2050	-0.1127	-0.0923	-0.2840	-0.1482	-0.1358	0.0801	0.0359	0.0442
market equity ratio (1)	*t*-statistic	(-14.54)	(-7.63)	(-15.28)	(-26.11)	(-10.25)	(-19.31)	(3.81)	(1.44)	(4.16)
IBES intrinsic value-to-	Average	-0.7773	-0.3108	-0.4665	-0.7600	-0.3126	-0.4474	-0.0080	0.0015	-0.0095
market equity ratio (2)	*t*-statistic	(-42.55)	(-23.02)	(-39.78)	(-29.12)	(-22.14)	(-23.87)	(-0.23)	(0.07)	(-0.41)
IBES intrinsic value-to-	Average	-0.8247	-0.3579	-0.4668	-0.8198	-0.3702	-0.4497	0.0046	0.0122	-0.0075
market equity ratio (3)	*t*-statistic	(-45.67)	(-25.91)	(-41.64)	(-32.05)	(-26.70)	(-25.37)	(0.14)	(0.55)	(-0.34)

Table 2.8

Cross-sectional average size-adjusted variable values following high and low sentiment. This table reports the cross-sectional average values for a collection of illiquidity and short sale constraint measures following high and low investor sentiment. Each June, I sort firms into 10 portfolios using 1 of the 50 trading strategy variables used in Bulsiewicz (2013). The extreme portfolio with firms that have the highest expected return is classified as the long leg while the other extreme portfolio is classified as the short leg. Starting with Amihud's illiquidity measure, I calculate the equally-weighted and value-weighted monthly average illiquidity for these 2 portfolios from July of year *t* until June of year *t+1*. Using these 2 time-series average portfolio illiquidity, I construct the long-short portfolio illiquidity as the difference between the monthly long leg and short leg portfolio illiquidity. I then calculate the average illiquidity, in percent form, following high and low investor sentiment by regressing the portfolio illiquidity series on the high and low sentiment indicator variable constructed using the Baker and Wurgler (2006) orthogonalized investor sentiment measure. I repeat these steps for the remaining 49 trading strategies. Using these estimates of illiquidity following high and low sentiment, I calculate the cross-sectional average illiquidity across all 50 trading strategies following high and low sentiment. This procedure is repeated for the remaining liquidity measures and for the additional short sale constraints measures. The results for Amihud's illiquidity, average percentage of zero trading days, Corwin-Schultz (2012) bid-ask spread, daily average dollar volume, share turnover, and trading volume, and Pastor and Stambaugh (2003) liquidity beta are presented in Panel A.1 and B.1. The results for the average return variance, forecast dispersion, idiosyncratic risk, institutional ownership, and short interest are presented in Panels A.2 and B.2. Panel A presents the results for equally-weighted portfolios and Panel B presents the results for value-weighted portfolios.

Panel A.1 Size-Adjusted Results

Panel A.1.1 Liquidity related variables

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
	Average	-1.5217	-2.5279	1.0062	-1.6547	-2.6804	1.0256	0.1326	0.1510	-0.0184
Amihud illiquidity	*t*-statistic	(-19.67)	(-17.50)	(14.20)	(-24.47)	(-22.43)	(15.05)	(1.02)	(0.63)	(-0.15)
Average percentage of	Average	-1.2908	-1.1179	-0.1729	-2.7262	-2.1309	-0.5953	1.4356	1.0122	0.4235
trading days with zero	*t*-statistic	(-5.81)	(-5.08)	(-2.82)	(-14.71)	(-10.05)	(-8.46)	(4.53)	(3.11)	(4.02)
Corwin-Schultz bid-ask	Average	-0.3896	-0.4935	0.1039	-0.3460	-0.4601	0.1142	-0.0439	-0.0341	-0.0098
spread	*t*-statistic	(-19.84)	(-19.84)	(14.23)	(-24.98)	(-21.98)	(12.87)	(-1.45)	(-0.82)	(-0.72)
	Average	3.3445	2.1690	1.1755	3.1590	1.8556	1.3034	0.1863	0.3176	-0.1314
Daily dollar volume	*t*-statistic	(3.60)	(3.54)	(3.19)	(6.34)	(6.99)	(4.96)	(0.15)	(0.42)	(-0.25)
	Average	0.0870	0.0807	0.0063	0.1456	0.1139	0.0317	-0.0586	-0.0331	-0.0254
Daily share turnover	*t*-statistic	(5.03)	(5.43)	(1.52)	(11.53)	(10.08)	(11.12)	(-2.29)	(-1.47)	(-4.36)
	Average	141.7588	132.4813	9.2774	155.8048	133.7632	22.0416	-14.0004	-1.0855	-12.9149
Daily volume	*t*-statistic	(3.26)	(3.14)	(1.05)	(7.84)	(7.80)	(3.02)	(-0.26)	(-0.02)	(-1.08)
Pastor-Stambaugh	Average	0.0442	0.0311	0.0131	-0.0331	-0.0268	-0.0063	0.0772	0.0577	0.0195
liquidity beta	*t*-statistic	(2.52)	(2.09)	(3.65)	(-1.87)	(-1.75)	(-1.68)	(2.20)	(1.92)	(2.86)

Panel A.2 Additional hard-to-short measures

Variable	Statistic	Long leg High	Long leg Low	Long leg High-Low	Short leg High	Short leg Low	Short leg High-Low	Long-Short High	Long-Short Low	Long-Short High-Low
	Average	-4.1458	-4.9457	0.7999	-1.3482	-3.4795	2.1313	-2.7969	-1.4704	-1.3265
Average return variance	*t*-statistic	(-9.32)	(-13.80)	(5.01)	(-3.30)	(-8.68)	(10.21)	(-3.82)	(-2.15)	(-4.67)
	Average	0.0549	0.0394	0.0154	0.1259	0.0903	0.0356	-0.0711	-0.0508	-0.0202
Forecast dispersion	*t*-statistic	(3.68)	(2.83)	(4.61)	(5.49)	(4.20)	(11.18)	(-2.05)	(-1.56)	(-3.78)
	Average	-0.1851	-0.2053	0.0202	0.0838	-0.0285	0.1123	-0.2688	-0.1769	-0.0919
Idiosyncratic risk	*t*-statistic	(-4.62)	(-6.41)	(1.80)	(2.37)	(-0.92)	(10.69)	(-4.21)	(-3.22)	(-5.40)
	Average	4.8328	6.2676	-1.4347	3.9055	5.2515	-1.3460	0.9272	1.0161	-0.0888
Institutional ownership	*t*-statistic	(18.71)	(19.17)	(-12.52)	(13.98)	(15.51)	(-11.70)	(2.22)	(1.94)	(-0.51)
	Average	0.2685	0.3032	-0.0347	0.3734	0.4309	-0.0575	-0.1049	-0.1277	0.0228
Short interest	*t*-statistic	(11.22)	(12.04)	(-2.74)	(12.66)	(11.68)	(-4.20)	(-2.70)	(-2.85)	(1.09)

Table 2.8 continued

Panel B. Value-weighted portfolios

Panel B.1 Liquidity related variables

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	-0.2104	-0.3488	0.1383	-0.2786	-0.4047	0.1260	0.0682	0.0560	0.0123
Amihud illiquidity	t-statistic	(-3.07)	(-2.87)	(2.59)	(-8.02)	(-6.63)	(3.73)	(0.81)	(0.38)	(0.18)
Average percentage of zero	Average	-0.4199	-0.3932	-0.0267	-0.6913	-0.4423	-0.2490	0.2715	0.0506	0.2210
trading days	t-statistic	(-4.45)	(-4.74)	(-0.92)	(-10.57)	(-4.33)	(-3.22)	(2.07)	(0.36)	(2.62)
	Average	-0.0484	-0.0706	0.0222	-0.0476	-0.0695	0.0219	-0.0009	-0.0013	0.0004
Corwin-Schultz bid-ask spread	t-statistic	(-3.11)	(-3.77)	(6.17)	(-4.89)	(-5.65)	(6.98)	(-0.05)	(-0.05)	(0.08)
	Average	77.5502	46.4857	31.0645	66.3552	38.5063	27.8489	11.2714	8.1943	3.0772
Daily dollar volume	t-statistic	(7.04)	(7.18)	(5.51)	(7.78)	(8.15)	(6.44)	(0.65)	(0.82)	(0.36)
	Average	0.0719	0.0659	0.0059	0.1611	0.1077	0.0534	-0.0893	-0.0420	-0.0473
Daily share turnover	t-statistic	(3.24)	(3.82)	(0.81)	(8.57)	(6.78)	(8.59)	(-2.78)	(-1.65)	(-4.33)
	Average	2405.8642	1669.9320	735.9321	2266.9946	1609.7846	657.2101	140.1514	63.4841	76.6674
Daily volume	t-statistic	(7.05)	(7.34)	(5.22)	(8.98)	(8.68)	(5.32)	(0.28)	(0.18)	(0.39)
Pastor-Stambaugh liquidity	Average	0.0166	0.0181	-0.0016	-0.0550	-0.0292	-0.0257	0.0715	0.0473	0.0242
beta	t-statistic	(1.11)	(1.49)	(-0.37)	(-4.00)	(-2.45)	(-6.53)	(2.52)	(1.97)	(3.54)

Panel B.2 Additional hard-to-short measures

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Average	0.2123	-0.0080	0.2203	2.2450	0.7922	1.4528	-2.0319	-0.8006	-1.2313
Average return variance	t-statistic	(0.67)	(-0.03)	(1.54)	(6.64)	(3.18)	(9.10)	(-4.36)	(-2.40)	(-5.16)
	Average	0.0508	0.0602	-0.0095	0.1550	0.1321	0.0229	-0.1045	-0.0719	-0.0326
Forecast dispersion	t-statistic	(3.86)	(3.60)	(-1.44)	(5.84)	(4.98)	(4.52)	(-3.05)	(-1.96)	(-3.51)
	Average	0.0525	0.0449	0.0076	0.2774	0.1737	0.1036	-0.2248	-0.1289	-0.0959
Idiosyncratic risk	t-statistic	(1.73)	(1.70)	(0.78)	(8.27)	(5.97)	(10.19)	(-4.97)	(-3.43)	(-6.12)
	Average	-0.2969	0.3104	-0.6073	-0.0159	0.3036	-0.3195	-0.2810	0.0068	-0.2878
Institutional ownership	t-statistic	(-0.79)	(0.67)	(-2.84)	(-0.05)	(0.99)	(-1.76)	(-0.52)	(0.01)	(-0.95)
	Average	0.0726	0.1456	-0.0729	0.2189	0.2511	-0.0322	-0.1462	-0.1055	-0.0407
Short interest	t-statistic	(2.75)	(4.58)	(-6.77)	(6.71)	(6.31)	(-2.03)	(-3.74)	(-2.22)	(-1.95)

Table 2.9

Cross-sectional average size-adjusted ownership following high and low sentiment by institution type. This table presents the cross-sectional average ownership across 50 trading strategies by financial institution type. Following the methodology outlined in Table 2.1, starting with percentage of outstanding shares held by banks, I calculate the time-series equally-weighted and value-weighted portfolio bank ownership for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average bank ownership following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross-sectional average bank ownership across all 50 trading strategies. These steps are repeated for insurance companies and other financial institutions. Ownership coefficients are reported as percentage of shares outstanding held by that particular institution type.

Panel A. Equally-weighted portfolios

Type of		Long leg			Short leg			Long-Short		
Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	0.5673	0.6373	-0.0700	-0.1001	0.0240	-0.1242	0.6674	0.6133	0.0542
	t-statistic	(5.47)	(6.41)	(-2.03)	(-1.17)	(0.22)	(-3.27)	(4.00)	(3.46)	(0.96)
Insurance	Average	0.1698	0.2866	-0.1167	0.2181	0.2234	-0.0053	-0.0483	0.0631	-0.1114
Companies	*t*-statistic	(5.95)	(8.21)	(-7.50)	(2.75)	(4.01)	(-0.18)	(-0.55)	(0.90)	(-2.94)
Other	Average	4.0873	5.3437	-1.2564	3.7827	5.0040	-1.2213	0.3046	0.3396	-0.0351
	t-statistic	(21.13)	(20.13)	(-13.19)	(16.88)	(19.21)	(-15.26)	(1.02)	(0.86)	(-0.26)

Panel B. Value-weighted portfolios

Type of		Long leg			Short leg			Long-Short		
Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	0.0121	-0.0071	0.0192	-1.1224	-1.0905	-0.0318	1.1344	1.0835	0.0509
	t-statistic	(0.08)	(-0.05)	(0.26)	(-8.21)	(-7.10)	(-0.49)	(4.61)	(4.39)	(0.51)
Insurance	Average	-0.1846	-0.0880	-0.0966	0.1323	0.1394	-0.0072	-0.3168	-0.2274	-0.0894
Companies	*t*-statistic	(-5.56)	(-2.43)	(-4.46)	(0.69)	(0.80)	(-0.27)	(-1.54)	(-1.19)	(-2.56)
Other	Average	-0.1302	0.4054	-0.5356	0.9757	1.2547	-0.2790	-1.1057	-0.8493	-0.2564
	t-statistic	(-0.32)	(0.79)	(-2.84)	(3.32)	(3.67)	(-2.00)	(-2.01)	(-1.24)	(-1.04)

Table 2.10

Cross-sectional average size-adjusted valuation following high and low sentiment. This table presents the cross-sectional average valuation across 50 trading strategies for a collection of valuation measures. Following the methodology outlined in Table 2.2, starting with analysts' expected returns, I calculate the time-series equally-weighted and value-weighted portfolio values for the long leg, short leg, and long-short portfolios. For each trading strategy, I then estimate the average analysts' expected return following high and low sentiment. After completing this estimation for all 50 trading strategies, I then calculate the cross-sectional average analysts' expected return across all fifty trading strategies. These steps are repeated for the remaining valuation measures. Analysts' expected return is calculated as the difference between analysts' most recent annual price target minus the stock's current share price scaled by the stock's current share price.

Panel A. Equally-weighted portfolios

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected	Average	-16.1235	-15.0259	-1.0976	6.2062	-9.9895	16.1956	-22.0226	-5.0466	-16.9760
return	*t*-statistic	(-6.54)	(-9.83)	(-0.71)	(2.96)	(-10.20)	(9.09)	(-5.61)	(-2.26)	(-6.01)
Average	Average	-0.0159	-0.0288	0.0129	-0.0508	-0.0477	-0.0031	0.0350	0.0190	0.0159
Recommendation	*t*-statistic	(-0.89)	(-1.83)	(3.12)	(-3.15)	(-3.05)	(-0.58)	(1.10)	(0.64)	(2.22)
	Average	-0.0318	-0.0472	0.0154	-0.0916	-0.1020	0.0104	0.0597	0.0544	0.0053
Book-to-market ratio	*t*-statistic	(-0.87)	(-1.20)	(2.46)	(-4.55)	(-4.44)	(1.46)	(1.14)	(0.97)	(0.45)
Compustat intrinsic	Average	-0.4707	-0.1773	-0.2934	-0.3327	-0.2105	-0.1222	-0.1384	0.0330	-0.1714
value-to-market	*t*-statistic	(-13.97)	(-6.56)	(-12.52)	(-10.52)	(-11.66)	(-3.62)	(-2.56)	(0.81)	(-3.42)
IBES intrinsic value-to-	Average	-0.2116	-0.0982	-0.1134	-0.2716	-0.1191	-0.1525	0.0600	0.0212	0.0387
market equity ratio (1)	*t*-statistic	(-12.33)	(-7.84)	(-11.60)	(-25.61)	(-11.94)	(-16.14)	(2.45)	(1.14)	(2.31)
IBES intrinsic value-to-	Average	-0.5297	-0.1740	-0.3557	-0.4638	-0.1086	-0.3552	-0.0618	-0.0657	0.0039
market equity ratio (2)	*t*-statistic	(-12.03)	(-12.66)	(-9.78)	(-15.17)	(-7.17)	(-11.91)	(-0.95)	(-3.23)	(0.07)
IBES intrinsic value-to-	Average	-0.5963	-0.2123	-0.3839	-0.5242	-0.1587	-0.3655	-0.0673	-0.0537	-0.0137
market equity ratio (3)	*t*-statistic	(-13.23)	(-13.41)	(-10.84)	(-16.08)	(-10.10)	(-13.26)	(-0.99)	(-2.26)	(-0.25)

Panel B. Value-weighted portfolios

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected	Average	7.7761	2.8075	4.9686	24.5938	5.8353	18.7584	-16.7490	-3.0215	-13.7275
return	*t*-statistic	(3.56)	(1.92)	(3.98)	(12.77)	(5.91)	(13.37)	(-5.56)	(-1.54)	(-6.78)
Average	Average	0.0009	-0.0154	0.0163	-0.0545	-0.0568	0.0022	0.0554	0.0413	0.0142
Recommendation	*t*-statistic	(0.06)	(-1.02)	(3.64)	(-3.14)	(-3.36)	(0.30)	(1.92)	(1.43)	(1.59)
	Average	-0.0193	-0.0020	-0.0173	-0.0340	-0.0406	0.0066	0.0143	0.0380	-0.0237
Book-to-market ratio	*t*-statistic	(-0.56)	(-0.05)	(-2.19)	(-1.61)	(-1.69)	(0.81)	(0.29)	(0.70)	(-1.92)
Compustat intrinsic	Average	0.0043	0.0174	-0.0131	0.0140	-0.0329	0.0469	-0.0097	0.0501	-0.0598
value-to-market	*t*-statistic	(0.14)	(0.69)	(-0.85)	(0.56)	(-2.12)	(1.57)	(-0.25)	(1.34)	(-1.73)
IBES intrinsic value-to-	Average	0.0054	0.0088	-0.0034	-0.0719	-0.0251	-0.0468	0.0768	0.0341	0.0427
market equity ratio (1)	*t*-statistic	(0.29)	(0.58)	(-0.34)	(-8.40)	(-2.01)	(-5.33)	(3.15)	(1.42)	(2.80)
IBES intrinsic value-to-	Average	-0.0162	0.0002	-0.0163	0.0034	-0.0028	0.0063	-0.0200	0.0031	-0.0231
market equity ratio (2)	*t*-statistic	(-0.46)	(0.01)	(-0.65)	(0.18)	(-0.30)	(0.39)	(-0.47)	(0.15)	(-0.75)
IBES intrinsic value-to-	Average	-0.0239	-0.0066	-0.0173	-0.0179	-0.0193	0.0014	-0.0064	0.0129	-0.0192
market equity ratio (3)	*t*-statistic	(-0.65)	(-0.39)	(-0.71)	(-0.98)	(-2.06)	(0.09)	(-0.15)	(0.58)	(-0.65)

Table 2.11

Difference in cross-sectional means between original strategies and additional strategies. This table reports the difference in the cross-sectional mean values between the original strategies and the additional strategies for the short sale constraint measures, valuation measures, and institutional ownership measures. The original strategies are the 16 strategies previously used in Stambaugh, Yu, and Yuan (2012b) while the new strategies are the 34 additional strategies considered in Bulsiewicz (2013, 2014). For each group of strategies, I calculate the cross-sectional mean value for a number of financial variables. Then using a two-sample *t*-test, I calculate if there is a statistical difference between the original strategies and the new strategies. Below Panel A presents the results for equally-weighted portfolios while Panel B presents the results for value-weighted portfolios.

Panel A. Equally-weighted portfolios

Panel A.1 Liquidity related variables

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Difference	0.0939	0.1240	-0.0301	-0.1615	-0.1392	-0.0223	0.2556	0.2634	-0.0078
Amihud illiquidity	*t*-statistic	(0.59)	(0.77)	(-0.19)	(-1.01)	(-0.87)	(-0.14)	(1.59)	(1.64)	(-0.05)
Average percentage of	Difference	1.4772	1.6043	-0.1271	-1.0025	-1.2157	0.2131	2.4776	2.8174	-0.3398
zero trading days	*t*-statistic	(2.14)	(2.32)	(-0.18)	(-1.45)	(-1.76)	(0.31)	(3.59)	(4.08)	(-0.49)
Corwin-Schultz bid-ask	Difference	0.0468	0.0433	0.0036	-0.0574	-0.0686	0.0112	0.1041	0.1113	-0.0072
spread	*t*-statistic	(0.71)	(0.65)	(0.05)	(-0.87)	(-1.04)	(0.17)	(1.57)	(1.68)	(-0.11)
	Difference	-2.6693	-1.8564	-0.8129	8.1105	5.2221	2.8885	-10.7979	-7.1282	-3.6697
Daily dollar volume	*t*-statistic	(-0.48)	(-0.34)	(-0.15)	(1.47)	(0.94)	(0.52)	(-1.95)	(-1.29)	(-0.66)
	Difference	-0.0571	-0.0553	-0.0017	0.0304	0.0117	0.0187	-0.0878	-0.0681	-0.0198
Daily share turnover	*t*-statistic	(-1.83)	(-1.78)	(-0.06)	(0.98)	(0.38)	(0.60)	(-2.82)	(-2.19)	(-0.64)
	Difference	-104.8029	-130.4034	25.6004	263.6256	216.2613	47.3643	-369.0502	-349.0224	-20.0278
Daily volume	*t*-statistic	(-0.53)	(-0.66)	(0.13)	(1.34)	(1.10)	(0.24)	(-1.87)	(-1.77)	(-0.10)
Pastor-Stambaugh	Difference	0.0209	0.0187	0.0021	-0.0243	-0.0210	-0.0033	0.0452	0.0399	0.0053
liquidity beta	*t*-statistic	(0.46)	(0.42)	(0.05)	(-0.54)	(-0.47)	(-0.07)	(1.01)	(0.89)	(0.12)

Panel A.2 Additional hard-to-short measures

Variable	Statistic	Long leg			Short leg			Long-Short		
		High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Difference	-1.0415	-0.8204	-0.2212	0.2820	-0.1489	0.4309	-1.3257	-0.6787	-0.6470
Average return variance	*t*-statistic	(-1.13)	(-0.89)	(-0.24)	(0.30)	(-0.16)	(0.47)	(-1.43)	(-0.73)	(-0.70)
	Difference	-0.0531	-0.0542	0.0011	-0.0111	-0.0114	0.0003	-0.0414	-0.0426	0.0012
Forecast dispersion	*t*-statistic	(-1.15)	(-1.17)	(0.02)	(-0.24)	(-0.25)	(0.01)	(-0.90)	(-0.92)	(0.03)
	Difference	-0.0947	-0.0843	-0.0104	0.0051	-0.0356	0.0406	-0.1000	-0.0497	-0.0503
Idiosyncratic risk	*t*-statistic	(-0.88)	(-0.78)	(-0.10)	(0.05)	(-0.33)	(0.38)	(-0.93)	(-0.46)	(-0.47)
	Difference	-1.9607	-1.7275	-0.2332	1.0454	0.8520	0.1933	-3.0061	-2.5795	-0.4266
Institutional ownership	*t*-statistic	(-1.08)	(-0.95)	(-0.13)	(0.57)	(0.47)	(0.11)	(-1.65)	(-1.42)	(-0.23)
	Difference	-0.1618	-0.1599	-0.0019	0.0240	0.0351	-0.0110	-0.1859	-0.1950	0.0091
Short interest	*t*-statistic	(-2.45)	(-2.42)	(-0.03)	(0.36)	(0.53)	(-0.17)	(-2.81)	(-2.95)	(0.14)

Table 2.11 continued

Panel A.3 Valuation measures

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected return	Difference	-5.4624	-2.0410	-3.4214	5.7374	-1.8050	7.5424	-11.0471	-0.2282	-10.8190
	t-statistic	(-0.94)	(-0.35)	(-0.59)	(0.99)	(-0.31)	(1.30)	(-1.90)	(-0.04)	(-1.86)
Average Recommendation	Difference	-0.0106	-0.0221	0.0115	-0.0268	-0.0196	-0.0072	0.0158	-0.0032	0.0190
	t-statistic	(-0.31)	(-0.65)	(0.34)	(-0.79)	(-0.58)	(-0.21)	(0.47)	(-0.09)	(0.56)
Book-to-market ratio	Difference	-0.0301	-0.0378	0.0076	-0.0361	-0.0280	-0.0080	0.0045	-0.0069	0.0114
	t-statistic	(-0.34)	(-0.42)	(0.09)	(-0.40)	(-0.31)	(-0.09)	(0.05)	(-0.08)	(0.13)
Compustat intrinsic value-to-market equity ratio	Difference	-0.0244	0.0049	-0.0294	0.1309	-0.0038	0.1347	-0.1553	0.0089	-0.1641
	t-statistic	(-0.40)	(0.08)	(-0.48)	(2.15)	(-0.06)	(2.21)	(-2.55)	(0.15)	(-2.69)
IBES intrinsic value-to-market equity ratio (1)	Difference	-0.0068	-0.0147	0.0080	0.0120	0.0326	-0.0206	-0.0178	-0.0477	0.0299
	t-statistic	(-0.26)	(-0.56)	(0.30)	(0.46)	(1.24)	(-0.78)	(-0.67)	(-1.81)	(1.13)
IBES intrinsic value-to-market equity ratio (2)	Difference	-0.0281	-0.0214	-0.0068	0.0799	0.0345	0.0455	-0.1068	-0.0559	-0.0509
	t-statistic	(-0.57)	(-0.43)	(-0.14)	(1.61)	(0.70)	(0.92)	(-2.16)	(-1.13)	(-1.03)
IBES intrinsic value-to-market equity ratio (3)	Difference	-0.0259	-0.0212	-0.0047	0.0849	0.0502	0.0347	-0.1099	-0.0717	-0.0382
	t-statistic	(-0.53)	(-0.44)	(-0.10)	(1.75)	(1.03)	(0.71)	(-2.26)	(-1.48)	(-0.79)

Panel A.4 Institutional ownership by type

		Long leg			Short leg			Long-Short		
Type of Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	-0.1625	-0.3303	0.1678	0.5815	0.4785	0.1030	-0.7441	-0.8089	0.0648
	t-statistic	(-0.25)	(-0.50)	(0.25)	(0.88)	(0.72)	(0.16)	(-1.12)	(-1.22)	(0.10)
Insurance Companies	Average	-0.2400	-0.2258	-0.0142	0.0886	0.0379	0.0506	-0.3286	-0.2638	-0.0648
	t-statistic	(-1.26)	(-1.19)	(-0.07)	(0.47)	(0.20)	(0.27)	(-1.73)	(-1.39)	(-0.34)
Other	Average	-1.5524	-1.1713	-0.3811	0.3787	0.3355	0.0431	-1.9311	-1.5069	-0.4242
	t-statistic	(-1.45)	(-1.09)	(-0.35)	(0.35)	(0.31)	(0.04)	(-1.80)	(-1.40)	(-0.39)

Table 2.11 continued

Panel B. Value-weighted portfolios

Panel B.1 Liquidity related variables

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Difference	0.0608	0.0886	-0.0279	-0.0585	-0.0432	-0.0153	0.1194	0.1321	-0.0127
Amihud illiquidity	*t*-statistic	(0.69)	(1.00)	(-0.32)	(-0.66)	(-0.49)	(-0.17)	(1.35)	(1.49)	(-0.14)
Average percentage of	Difference	0.3569	0.3867	-0.0298	-0.3130	-0.4824	0.1694	0.6698	0.8693	-0.1995
zero trading days	*t*-statistic	(1.05)	(1.13)	(-0.09)	(-0.92)	(-1.41)	(0.50)	(1.96)	(2.55)	(-0.58)
Corwin-Schultz bid-ask	Difference	0.0256	0.0209	0.0048	-0.0197	-0.0242	0.0045	0.0455	0.0454	0.0001
spread	*t*-statistic	(0.56)	(0.46)	(0.10)	(-0.43)	(-0.53)	(0.10)	(1.00)	(0.99)	(0.00)
	Difference	28.2786	19.6193	8.6593	5.1826	-0.2143	5.3969	22.8787	19.2616	3.6171
Daily dollar volume	*t*-statistic	(1.09)	(0.75)	(0.33)	(0.20)	(-0.01)	(0.21)	(0.88)	(0.74)	(0.14)
	Difference	-0.0861	-0.0836	-0.0024	0.0223	0.0030	0.0194	-0.1087	-0.0872	-0.0215
Daily share turnover	*t*-statistic	(-2.24)	(-2.18)	(-0.06)	(0.58)	(0.08)	(0.51)	(-2.83)	(-2.27)	(-0.56)
	Difference	689.9977	440.5807	249.4170	42.2719	144.2443	-101.9724	642.7385	281.7391	360.9994
Daily volume	*t*-statistic	(0.90)	(0.58)	(0.33)	(0.06)	(0.19)	(-0.13)	(0.84)	(0.37)	(0.47)
Pastor-Stambaugh	Difference	0.0166	0.0133	0.0033	-0.0206	-0.0136	-0.0070	0.0372	0.0271	0.0102
liquidity beta	*t*-statistic	(0.45)	(0.36)	(0.09)	(-0.55)	(-0.37)	(-0.19)	(1.00)	(0.73)	(0.27)

Panel B.2 Additional hard-to-short measures

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
	Difference	-0.8744	-0.6727	-0.2017	0.3708	-0.0721	0.4429	-1.2462	-0.5995	-0.6467
Average return variance	*t*-statistic	(-1.02)	(-0.79)	(-0.24)	(0.43)	(-0.08)	(0.52)	(-1.46)	(-0.70)	(-0.76)
	Difference	-0.0412	-0.0508	0.0096	0.0070	0.0090	-0.0020	-0.0474	-0.0597	0.0123
Forecast dispersion	*t*-statistic	(-0.81)	(-0.99)	(0.19)	(0.14)	(0.18)	(-0.04)	(-0.93)	(-1.17)	(0.24)
	Difference	-0.1138	-0.1147	0.0009	0.0183	-0.0329	0.0512	-0.1321	-0.0813	-0.0509
Idiosyncratic risk	*t*-statistic	(-0.99)	(-1.00)	(0.01)	(0.16)	(-0.29)	(0.45)	(-1.15)	(-0.71)	(-0.44)
	Difference	-1.2275	-1.7530	0.5255	0.5605	0.9752	-0.4147	-1.7880	-2.7281	0.9402
Institutional ownership	*t*-statistic	(-0.89)	(-1.28)	(0.38)	(0.41)	(0.71)	(-0.30)	(-1.30)	(-1.99)	(0.68)
	Difference	-0.1927	-0.2441	0.0514	-0.0027	0.0383	-0.0410	-0.1900	-0.2824	0.0924
Short interest	*t*-statistic	(-2.17)	(-2.75)	(0.58)	(-0.03)	(0.43)	(-0.46)	(-2.14)	(-3.18)	(1.04)

Table 2.11 continued

Panel B.3 Valuation measures

		Long leg			Short leg			Long-Short		
Variable	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Analysts' expected return	Average	-4.1041	-1.1511	-2.9529	1.4624	0.8533	0.6091	-5.4866	-1.9995	-3.4872
	t-statistic	(-0.87)	(-0.24)	(-0.62)	(0.31)	(0.18)	(0.13)	(-1.16)	(-0.42)	(-0.74)
Average Recommendation	Average	-0.0233	-0.0341	0.0108	-0.0445	-0.0340	-0.0105	0.0208	-0.0003	0.0211
	t-statistic	(-0.72)	(-1.05)	(0.33)	(-1.37)	(-1.05)	(-0.32)	(0.64)	(-0.01)	(0.65)
Book-to-market ratio	Average	-0.0438	-0.0685	0.0247	-0.0042	0.0126	-0.0168	-0.0423	-0.0787	0.0364
	t-statistic	(-0.50)	(-0.77)	(0.28)	(-0.05)	(0.14)	(-0.19)	(-0.48)	(-0.89)	(0.41)
Compustat intrinsic value-to-market equity ratio	Average	0.0058	0.0085	-0.0027	0.0130	-0.0137	0.0267	-0.0075	0.0222	-0.0297
	t-statistic	(0.09)	(0.13)	(-0.04)	(0.19)	(-0.20)	(0.40)	(-0.11)	(0.33)	(-0.44)
IBES intrinsic value-to-market equity ratio (1)	Average	0.0073	0.0011	0.0062	-0.0140	0.0152	-0.0293	0.0214	-0.0146	0.0360
	t-statistic	(0.29)	(0.04)	(0.25)	(-0.57)	(0.62)	(-1.18)	(0.87)	(-0.59)	(1.46)
IBES intrinsic value-to-market equity ratio (2)	Average	-0.0071	0.0126	-0.0197	0.0087	0.0077	0.0010	-0.0151	0.0045	-0.0196
	t-statistic	(-0.17)	(0.30)	(-0.48)	(0.21)	(0.19)	(0.02)	(-0.37)	(0.11)	(-0.48)
IBES intrinsic value-to-market equity ratio (3)	Average	-0.0062	0.0136	-0.0198	0.0103	0.0129	-0.0025	-0.0164	0.0003	-0.0168
	t-statistic	(-0.16)	(0.34)	(-0.50)	(0.26)	(0.32)	(-0.06)	(-0.41)	(0.01)	(-0.42)

Panel B.4 Institutional ownership by type

		Long leg			Short leg			Long-Short		
Type of Institution	Statistic	High	Low	High-Low	High	Low	High-Low	High	Low	High-Low
Banks	Average	0.8405	0.4957	0.3448	0.2705	0.3622	-0.0917	0.5700	0.1335	0.4365
	t-statistic	(1.00)	(0.59)	(0.41)	(0.32)	(0.43)	(-0.11)	(0.68)	(0.16)	(0.52)
Insurance Companies	Average	-0.1240	-0.1342	0.0102	-0.1127	-0.1181	0.0054	-0.0113	-0.0160	0.0047
	t-statistic	(-0.60)	(-0.65)	(0.05)	(-0.54)	(-0.57)	(0.03)	(-0.05)	(-0.08)	(0.02)
Other	Average	-1.9218	-2.1146	0.1928	0.3950	0.7310	-0.3360	-2.3168	-2.8456	0.5288
	t-statistic	(-2.10)	(-2.31)	(0.21)	(0.43)	(0.80)	(-0.37)	(-2.53)	(-3.11)	(0.58)

Table 2.12

Average percentage of significant coefficients after double sorting on trading strategy and hard-to-short measures. Each June, I sort firms on each trading strategy variable into 5 quintile portfolios. I further divide the long leg and short leg portfolios of each trading strategy into 5 quintile hard-to-short portfolios using each hard-to-short measure. Then for both the long leg and short portfolios, I calculate value-weighted portfolio returns for the easy-to-short, hard-to-short, and the easy-to-short minus hard-to-short portfolios. Using each sentiment measure I test if the average excess return for each of these portfolios is significantly different between high and low sentiment and if future excess returns can be predicted using lagged investor sentiment. The 6 sentiment measures are: Baker and Wurgler (2006) orthogonalized investor sentiment (BWOIS), Baker and Wurgler (2006) investor sentiment (BWIS), the University of Michigan consumer confidence index (UMICH), the residual from a regression of the University of Michigan C.C. index on the 6 sentiment variables used in Baker and Wurgler (2006) (UMICHRESSENT), the residual from a regression of University of Michigan C.C. on the 6 economic growth variables (UMICHRESGDPGRO), and the residual from a regression of University of Michigan C.C. on the 6 economic levels variables (UMICHRESGDPLEV). For each hard-to-short measure, I then calculate the percentage of coefficients that are statistically significant. Finally, I calculate the cross-sectional average percentage of coefficients that are statistically significant for each sentiment measure. The 16 trading friction measures are analyst coverage, average rank, book-to-market ratio, cash flow-to-average assets ratio, Corwin-Schultz bid-ask spread, days to cover ratio, dollar short interest, forecast dispersion, institutional ownership, Pastor and Stambaugh (2003) liquidity beta, momentum, share turnover, short interest, short-term reversal (1), short-term reversal (2), and volatility.

Panel A. Average percentage of statistically significant high-low average return coefficients

Sentiment measure	Portfolio leg	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
		Easiest-to-Short	Hardest-to-short	ETS - HTS	Easiest-to-Short	Hardest-to-short	ETS - HTS
Baker and Wurgler investor sentiment	Long leg	1.01%	10.21%	13.99%	12.26%	15.75%	8.68%
	Short leg	7.95%	32.91%	25.53%	22.97%	38.85%	19.32%
Baker and Wurgler orthogonalized investor sentiment	Long leg	12.78%	33.38%	18.94%	13.55%	17.12%	9.89%
	Short leg	27.07%	56.61%	26.31%	25.28%	37.99%	19.00%
University of Michigan consumer confidence	Long leg	1.01%	19.23%	16.76%	2.41%	14.70%	8.19%
	Short leg	6.55%	42.08%	21.83%	10.36%	36.86%	13.64%
University of Michigan residual consumer confidence using economic growth	Long leg	0.89%	6.82%	11.38%	3.79%	10.81%	6.58%
	Short leg	1.26%	13.79%	11.56%	6.82%	20.17%	8.77%
University of Michigan residual consumer confidence using economic level variables	Long leg	35.97%	73.15%	23.42%	2.63%	11.07%	6.42%
	Short leg	49.85%	84.56%	26.85%	6.43%	23.01%	10.93%
University of Michigan residual consumer confidence using sentiment variables	Long leg	15.35%	54.86%	13.54%	3.02%	13.79%	7.74%
	Short leg	40.58%	75.69%	17.07%	11.36%	26.72%	8.98%

Panel B. Average percentage of statistically significant predictive regression coefficients

Sentiment measure	Portfolio leg	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
		Easiest-to-Short	Hardest-to-short	ETS - HTS	Easiest-to-Short	Hardest-to-short	ETS - HTS
Baker and Wurgler investor sentiment	Long leg	16.06%	40.62%	23.51%	17.52%	19.22%	11.60%
	Short leg	26.29%	55.76%	28.83%	24.29%	39.07%	21.56%
Baker and Wurgler orthogonalized investor sentiment	Long leg	21.41%	44.86%	23.41%	17.78%	18.33%	12.90%
	Short leg	32.80%	59.96%	28.85%	26.07%	35.92%	21.83%
University of Michigan consumer confidence	Long leg	0.63%	11.66%	14.12%	3.27%	19.08%	10.82%
	Short leg	1.77%	23.08%	17.92%	9.23%	37.61%	12.96%
University of Michigan residual consumer confidence using economic growth	Long leg	11.46%	47.72%	15.78%	3.67%	10.32%	7.33%
	Short leg	28.00%	76.43%	19.15%	6.84%	27.98%	11.07%
University of Michigan residual consumer confidence using economic level variables	Long leg	42.99%	73.45%	22.52%	11.57%	19.04%	9.85%
	Short leg	55.45%	88.18%	27.86%	15.39%	41.31%	12.46%
University of Michigan residual consumer confidence using sentiment variables	Long leg	31.94%	69.81%	17.36%	3.64%	16.64%	9.71%
	Short leg	54.63%	86.50%	19.36%	9.70%	43.47%	11.10%

Table 2.13

Number of significant average return coefficients for value-weighted portfolios formed by sorting firms on hard-to-short measures. Each June, I sort firms into decile portfolios using each of the 16 short sale constraint variables. Each portfolio is held from July of year *t* until June of year *t+1*. Value-weighted returns are calculated for each portfolio. Using each sentiment measure I test if the average excess return for each of these portfolios is significantly different between high and low sentiment and if future excess returns can be predicted using lagged investor sentiment. The 6 sentiment measures are: Baker and Wurgler (2006) orthogonalized investor sentiment (BWOIS), Baker and Wurgler (2006) investor sentiment (BWIS), the University of Michigan consumer confidence index (UMICH), the residual from a regression of the University of Michigan C.C. index on the 6 sentiment variables used in Baker and Wurgler (2006) (UMICHRESSENT), the residual from a regression of University of Michigan C.C. on the 6 economic growth variables (UMICHRESGDPGRO), and the residual from a regression of University of Michigan C.C. on the 6 economic levels variables (UMICHRESGDPLEV). After testing the long leg, short leg, and long-short portfolio for each short sale constraint measure, I then calculate the number and percentage of coefficients that are statistically significant. Below, Panel A presents the number and percentage of statistically significant high-low sentiment coefficients across all 16 strategies while Panel B presents the number and percentage of statistically significant predictive regression coefficients. The 16 trading friction measures are analyst coverage, average rank, book-to-market ratio, cash flow-to-average assets ratio, Corwin-Schultz bid-ask spread, days to cover ratio, dollar short interest, forecast dispersion, institutional ownership, Pastor and Stambaugh (2003) liquidity beta, momentum, share turnover, short interest, short-term reversal (1), short-term reversal (2), and volatility.

Panel A. Number and percentage of statistically significant high-low investor sentiment average returns coefficients

Sentiment Measure	Portfolio	Number of Strategies	Without controlling for Fama and French (1993) Factors				After controlling for Fama and French (1993) Factors			
			Number of statistically significant coefficients	Number of statistically significant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically significant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
Baker and Wurgler investor sentiment	Hardest-to-short	16	6	10	37.50%	62.50%	7	9	43.75%	56.25%
	Easiest-to-short	16	0	16	0.00%	100.00%	3	13	18.75%	81.25%
	HTS-ETS	16	7	9	43.75%	56.25%	5	11	31.25%	68.75%
Baker and Wurgler orthogonalized investor sentiment	Hardest-to-short	16	11	5	68.75%	31.25%	10	6	62.50%	37.50%
	Easiest-to-short	16	1	15	6.25%	93.75%	3	13	18.75%	81.25%
	HTS-ETS	16	5	11	31.25%	68.75%	5	11	31.25%	68.75%
University of Michigan consumer confidence	Hardest-to-short	16	9	7	56.25%	43.75%	8	8	50.00%	50.00%
	Easiest-to-short	16	0	16	0.00%	100.00%	0	16	0.00%	100.00%
	HTS-ETS	16	6	10	37.50%	62.50%	5	11	31.25%	68.75%
University of Michigan residual consumer confidence using economic growth variables	Hardest-to-short	16	2	14	12.50%	87.50%	3	13	18.75%	81.25%
	Easiest-to-short	16	0	16	0.00%	100.00%	0	16	0.00%	100.00%
	HTS-ETS	16	3	13	18.75%	81.25%	3	13	18.75%	81.25%
University of Michigan residual consumer confidence using economic level variables	Hardest-to-short	16	13	3	81.25%	18.75%	5	11	31.25%	68.75%
	Easiest-to-short	16	8	8	50.00%	50.00%	0	16	0.00%	100.00%
	HTS-ETS	16	7	9	43.75%	56.25%	3	13	18.75%	81.25%
University of Michigan residual consumer confidence using sentiment variables	Hardest-to-short	16	12	4	75.00%	25.00%	5	11	31.25%	68.75%
	Easiest-to-short	16	3	13	18.75%	81.25%	0	16	0.00%	100.00%
	HTS-ETS	16	4	12	25.00%	75.00%	2	14	12.50%	87.50%

Table 2.13 continued

Panel B. Number and percentage of statistically significant predictive regression coefficients

Sentiment Measure	Portfolio	Number of Strategies	Without controlling for Fama and French (1993) Factors				After controlling for Fama and French (1993) Factors			
			Number of statistically significant coefficients	Number of statistically significant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients	Number of statistically significant coefficients	Number of statistically significant coefficients	Percentage of statistically significant coefficients	Percentage of statistically insignificant coefficients
Baker and Wurgler investor sentiment	Hardest-to-short	16	10	6	62.50%	37.50%	8	8	50.00%	50.00%
	Easiest-to-short	16	3	13	18.75%	81.25%	2	14	12.50%	87.50%
	HTS-ETS	16	7	9	43.75%	56.25%	7	9	43.75%	56.25%
Baker and Wurgler orthogonalized investor sentiment	Hardest-to-short	16	10	6	62.50%	37.50%	7	9	43.75%	56.25%
	Easiest-to-short	16	5	11	31.25%	68.75%	3	13	18.75%	81.25%
	HTS-ETS	16	6	10	37.50%	62.50%	7	9	43.75%	56.25%
University of Michigan consumer confidence	Hardest-to-short	16	6	10	37.50%	62.50%	5	11	31.25%	68.75%
	Easiest-to-short	16	0	16	0.00%	100.00%	0	16	0.00%	100.00%
	HTS-ETS	16	6	10	37.50%	62.50%	4	12	25.00%	75.00%
University of Michigan residual consumer confidence using economic growth variables	Hardest-to-short	16	14	2	87.50%	12.50%	5	11	31.25%	68.75%
	Easiest-to-short	16	0	16	0.00%	100.00%	0	16	0.00%	100.00%
	HTS-ETS	16	5	11	31.25%	68.75%	3	13	18.75%	81.25%
University of Michigan residual consumer confidence using economic level variables	Hardest-to-short	16	14	2	87.50%	12.50%	9	7	56.25%	43.75%
	Easiest-to-short	16	9	7	56.25%	43.75%	0	16	0.00%	100.00%
	HTS-ETS	16	8	8	50.00%	50.00%	3	13	18.75%	81.25%
University of Michigan residual consumer confidence using sentiment variables	Hardest-to-short	16	14	2	87.50%	12.50%	7	9	43.75%	56.25%
	Easiest-to-short	16	7	9	43.75%	56.25%	0	16	0.00%	100.00%
	HTS-ETS	16	7	9	43.75%	56.25%	4	12	25.00%	75.00%

Table 2.14

Percent of statistically significant investor sentiment coefficients. This table shows the average percentage of statistically significant investor sentiment coefficients after excluding firms that are hard-to-short. Starting with the first trading strategy, firms are sorted on the trading strategy variable into 10 decile portfolios using NYSE breakpoints. Independent of the trading strategy sort, firms are sorted on 1 of the hard-to-short proxies and assigned to 1 of 5 quintile portfolios. Quintile portfolios are formed using 20% NYSE breakpoints. For analyst coverage, the hardest-to-short quintile is defined as firms with no analyst coverage. For the days to cover ratio, dollar short interest, and short interest we place all firms with 0 shares sold short into 1 portfolio and then allocate the remaining firms into 4 portfolios using 25% breakpoints. From the long leg and short leg portfolios, firms in the hardest-to-short quintile are removed and equally-weighted and value-weighted portfolio returns are calculated. This procedure is repeated for the 48 remaining trading strategies, excluding the combination strategy. The combination strategy is calculated after calculating returns for the first 11 trading strategies. Then, portfolio returns are regressed on the investor sentiment variables and the percentage of statistically significant coefficients is calculated. This procedure is repeated for the 15 remaining hard-to-short proxies. Finally, the average percentage of statistically significant coefficients is calculated across all 16 hard-to-short measures. This methodology is used for each of the sentiment measures. The table reports the percentage of statistically significant coefficients without excluding any securities, the cross-sectional average percentage of statistically significant coefficients after excluding securities in the hardest-to-short quintile, and the percentage of statistically significant coefficients after excluding securities of the smallest market capitalization quintile.

Panel A. Percentage of statistically significant High- Low Coefficients

Panel A.1 Equally-weighted portfolios

Sentiment measure	Exclusion Criteria	Without Fama and French			With Fama and French factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Baker and Wurgler investor sentiment	No exclusions	14.00%	80.00%	46.00%	46.00%	86.00%	44.00%
	Exclude hard-to-short securities	6.17%	61.20%	43.83%	25.78%	70.51%	37.03%
	Exclude small securities	14.00%	80.00%	46.00%	46.00%	86.00%	44.00%
Baker and Wurgler orthogonalized investor sentiment	No exclusions	30.00%	86.00%	46.00%	42.00%	80.00%	44.00%
	Exclude hard-to-short securities	24.68%	80.12%	37.90%	21.76%	61.68%	34.38%
	Exclude small securities	30.00%	86.00%	46.00%	42.00%	80.00%	44.00%
University of Michigan consumer confidence	No exclusions	12.00%	86.00%	54.00%	10.00%	78.00%	44.00%
	Exclude hard-to-short securities	0.25%	17.20%	23.66%	0.88%	18.94%	17.23%
	Exclude small securities	12.00%	86.00%	54.00%	10.00%	78.00%	44.00%
University of Michigan residual consumer confidence using economic growth variables	No exclusions	0.00%	10.00%	26.00%	0.00%	22.00%	18.00%
	Exclude hard-to-short securities	96.60%	96.22%	35.40%	5.65%	40.38%	14.24%
	Exclude small securities	0.00%	10.00%	26.00%	0.00%	22.00%	18.00%
University of Michigan residual consumer confidence using economic level variables	No exclusions	98.00%	96.00%	36.00%	4.00%	50.00%	16.00%
	Exclude hard-to-short securities	21.59%	81.03%	29.08%	0.88%	12.20%	15.62%
	Exclude small securities	98.00%	96.00%	36.00%	4.00%	50.00%	16.00%
University of Michigan residual consumer confidence using sentiment variables	No exclusions	28.00%	88.00%	36.00%	0.00%	8.00%	18.00%
	Exclude hard-to-short securities	10.29%	71.72%	45.22%	7.17%	57.02%	34.01%
	Exclude small securities	28.00%	88.00%	36.00%	0.00%	8.00%	18.00%

Panel A.2 Value-weighted portfolios

Sentiment measure	Exclusion Criteria	Without Fama and French			With Fama and French factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Baker and Wurgler investor sentiment	No exclusions	2.00%	34.00%	44.00%	18.00%	62.00%	40.00%
	Exclude hard-to-short securities	1.89%	28.72%	37.55%	14.33%	48.86%	31.50%
	Exclude small securities	2.00%	34.00%	44.00%	18.00%	62.00%	40.00%
Baker and Wurgler orthogonalized investor sentiment	No exclusions	12.50%	75.00%	62.50%	18.75%	81.25%	56.25%
	Exclude hard-to-short securities	12.34%	59.20%	30.50%	14.22%	48.72%	23.80%
	Exclude small securities	8.00%	62.00%	38.00%	16.00%	64.00%	30.00%
University of Michigan consumer confidence	No exclusions	2.00%	40.00%	34.00%	10.00%	48.00%	28.00%
	Exclude hard-to-short securities	1.39%	14.85%	22.41%	10.83%	33.08%	17.49%
	Exclude small securities	2.00%	40.00%	34.00%	10.00%	48.00%	28.00%
University of Michigan residual consumer confidence using economic growth variables	No exclusions	0.00%	10.00%	24.00%	12.00%	34.00%	16.00%
	Exclude hard-to-short securities	44.34%	82.74%	27.59%	3.40%	26.16%	12.06%
	Exclude small securities	0.00%	10.00%	24.00%	12.00%	34.00%	16.00%
University of Michigan residual consumer confidence using economic level variables	No exclusions	46.00%	86.00%	32.00%	2.00%	38.00%	18.00%
	Exclude hard-to-short securities	23.14%	78.91%	31.59%	7.18%	42.03%	19.76%
	Exclude small securities	46.00%	86.00%	32.00%	2.00%	38.00%	18.00%
University of Michigan residual consumer confidence using sentiment variables	No exclusions	12.50%	87.50%	56.25%	0.00%	75.00%	50.00%
	Exclude hard-to-short securities	3.14%	29.78%	30.33%	7.55%	38.86%	21.26%
	Exclude small securities	30.00%	86.00%	34.00%	8.00%	52.00%	24.00%

Table 2.14 continued

Panel B. Percentage of statistically significant predictive regression coefficients

Panel B.1 Equally-weighted portfolios

Sentiment measure	Exclusion Criteria	Without Fama and French			With Fama and French factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Baker and Wurgler investor sentiment	No exclusions	62.00%	88.00%	44.00%	42.00%	76.00%	42.00%
	Exclude hard-to-short securities	36.66%	72.22%	41.07%	26.53%	55.61%	33.76%
	Exclude small securities	62.00%	88.00%	44.00%	42.00%	76.00%	42.00%
Baker and Wurgler orthogonalized investor sentiment	No exclusions	66.00%	88.00%	44.00%	36.00%	70.00%	40.00%
	Exclude hard-to-short securities	37.42%	72.02%	41.70%	22.13%	48.05%	33.37%
	Exclude small securities	66.00%	88.00%	44.00%	36.00%	70.00%	40.00%
University of Michigan consumer confidence	No exclusions	10.00%	68.00%	50.00%	16.00%	66.00%	34.00%
	Exclude hard-to-short securities	45.00%	88.78%	37.16%	0.75%	17.45%	21.30%
	Exclude small securities	10.00%	68.00%	50.00%	16.00%	66.00%	34.00%
University of Michigan residual consumer confidence using economic growth variables	No exclusions	60.00%	94.00%	44.00%	0.00%	26.00%	18.00%
	Exclude hard-to-short securities	93.81%	96.35%	40.29%	27.41%	72.13%	22.41%
	Exclude small securities	60.00%	94.00%	44.00%	0.00%	26.00%	18.00%
University of Michigan residual consumer confidence using economic level variables	No exclusions	96.00%	96.00%	46.00%	34.00%	82.00%	26.00%
	Exclude hard-to-short securities	71.79%	91.27%	39.04%	4.53%	37.76%	25.96%
	Exclude small securities	96.00%	96.00%	46.00%	34.00%	82.00%	26.00%
University of Michigan residual consumer confidence using sentiment variables	No exclusions	93.75%	100.00%	62.50%	0.00%	62.50%	43.75%
	Exclude hard-to-short securities	4.90%	55.21%	41.05%	12.58%	55.51%	29.48%
	Exclude small securities	88.00%	96.00%	50.00%	4.00%	42.00%	30.00%

Panel B.2 Value-weighted portfolios

Sentiment measure	Exclusion Criteria	Without Fama and French			With Fama and French factors		
		Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Baker and Wurgler investor sentiment	No exclusions	34.00%	68.00%	40.00%	30.00%	62.00%	40.00%
	Exclude hard-to-short securities	17.90%	58.95%	35.02%	17.61%	47.22%	29.34%
	Exclude small securities	34.00%	68.00%	40.00%	30.00%	62.00%	40.00%
Baker and Wurgler orthogonalized investor sentiment	No exclusions	40.00%	74.00%	44.00%	20.00%	60.00%	38.00%
	Exclude hard-to-short securities	23.32%	66.03%	37.66%	14.35%	44.58%	30.11%
	Exclude small securities	40.00%	74.00%	44.00%	20.00%	60.00%	38.00%
University of Michigan consumer confidence	No exclusions	2.00%	24.00%	38.00%	12.00%	50.00%	28.00%
	Exclude hard-to-short securities	21.39%	74.67%	32.23%	9.20%	39.28%	21.78%
	Exclude small securities	2.00%	24.00%	38.00%	12.00%	50.00%	28.00%
University of Michigan residual consumer confidence using economic growth variables	No exclusions	30.00%	84.00%	34.00%	10.00%	48.00%	26.00%
	Exclude hard-to-short securities	44.29%	84.73%	32.99%	15.85%	50.36%	20.13%
	Exclude small securities	30.00%	84.00%	34.00%	10.00%	48.00%	26.00%
University of Michigan residual consumer confidence using economic level variables	No exclusions	54.00%	88.00%	36.00%	18.00%	68.00%	28.00%
	Exclude hard-to-short securities	36.59%	82.55%	37.24%	6.04%	49.83%	25.94%
	Exclude small securities	54.00%	88.00%	36.00%	18.00%	68.00%	28.00%
University of Michigan residual consumer confidence using sentiment variables	No exclusions	46.00%	94.00%	42.00%	8.00%	62.00%	36.00%
	Exclude hard-to-short securities	1.25%	15.21%	29.08%	9.82%	43.79%	22.02%
	Exclude small securities	46.00%	94.00%	42.00%	8.00%	62.00%	36.00%

Table 2.15

Percentage of statistically significant coefficients after excluding hardest-to-short quintile using Baker and Wurgler (2006) orthogonalized investor sentiment. This table shows the percentage of statistically significant coefficients across all 50 trading strategies for each of the 16 hard-to-short measures. The methodology used in calculating the percentage of statistically significant coefficients is described in Table 2.12. The high-low coefficients are the average difference between high and low sentiment and are estimated by regressing excess returns on a constant and a high sentiment dummy variable. The high sentiment dummy variable takes a value of 1 if the prior period had sentiment above the median level of investor sentiment over the full sample. Otherwise the dummy variable takes a value of 0. The predictive regression coefficients are the slope coefficient from regressing excess returns on a constant and lagged investor sentiment.

Panel A: Average percentage of high-low sentiment coefficients

Panel A.1: Equally-weighted portfolios

	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
Hard-to-short measure	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Analyst coverage	32.65%	91.84%	34.69%	8.16%	55.10%	30.61%
Average rank	6.00%	64.00%	34.00%	12.00%	46.00%	34.00%
Book-to-market ratio	8.16%	69.39%	32.65%	18.37%	38.78%	28.57%
Cash flow-to-average assets	12.00%	48.00%	24.00%	18.00%	30.00%	20.00%
Corwin-Schultz bid-ask spread	30.00%	84.00%	40.00%	36.00%	84.00%	38.00%
Days to cover	48.00%	94.00%	40.00%	30.00%	80.00%	40.00%
Dollar short interest	44.00%	92.00%	44.00%	32.00%	82.00%	40.00%
Forecast dispersion	36.73%	87.76%	38.78%	6.12%	46.94%	26.53%
Institutional ownership	10.00%	84.00%	40.00%	6.00%	40.00%	26.00%
Liquidity beta	26.53%	81.63%	42.86%	26.53%	71.43%	42.86%
Momentum	22.45%	81.63%	30.61%	28.57%	69.39%	30.61%
Share turnover	18.00%	78.00%	36.00%	24.00%	70.00%	34.00%
Short interest	46.00%	92.00%	46.00%	28.00%	82.00%	44.00%
Short-term reversal (1)	16.33%	85.71%	42.86%	22.45%	61.22%	42.86%
Short-term reversal (2)	32.00%	86.00%	38.00%	40.00%	74.00%	32.00%
Volatility	6.00%	62.00%	42.00%	12.00%	56.00%	40.00%

Panel A.2: Value-weighted portfolios

	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
Hard-to-short measure	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Analyst coverage	24.49%	87.76%	36.73%	10.20%	55.10%	22.45%
Average rank	4.00%	44.00%	26.00%	14.00%	42.00%	20.00%
Book-to-market ratio	2.04%	48.98%	36.73%	8.16%	44.90%	30.61%
Cash flow-to-average assets	8.00%	34.00%	22.00%	14.00%	36.00%	24.00%
Corwin-Schultz bid-ask spread	6.00%	64.00%	38.00%	14.00%	64.00%	34.00%
Days to cover	20.00%	78.00%	30.00%	20.00%	66.00%	22.00%
Dollar short interest	28.00%	88.00%	34.00%	28.00%	74.00%	32.00%
Forecast dispersion	26.53%	77.55%	26.53%	10.20%	26.53%	16.33%
Institutional ownership	24.00%	80.00%	32.00%	8.00%	28.00%	16.00%
Liquidity beta	6.12%	53.06%	34.69%	16.33%	55.10%	26.53%
Momentum	6.12%	48.98%	32.65%	12.24%	48.98%	20.41%
Share turnover	6.00%	40.00%	28.00%	8.00%	40.00%	20.00%
Short interest	20.00%	78.00%	34.00%	20.00%	66.00%	30.00%
Short-term reversal (1)	6.12%	42.86%	32.65%	16.33%	46.94%	22.45%
Short-term reversal (2)	4.00%	42.00%	22.00%	14.00%	42.00%	22.00%
Volatility	6.00%	40.00%	22.00%	14.00%	44.00%	22.00%

Table 2.15 continued

Panel B: Average percentage of statistically significant predictive regression coefficients

Panel B.1: Equally-weighted portfolios

	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
Hard-to-short measure	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Analyst coverage	8.16%	55.10%	30.61%	2.04%	2.04%	24.49%
Average rank	12.00%	46.00%	34.00%	16.00%	52.00%	30.00%
Book-to-market ratio	18.37%	38.78%	28.57%	24.49%	55.10%	32.65%
Cash flow-to-average assets	18.00%	30.00%	20.00%	30.00%	42.00%	20.00%
Corwin-Schultz bid-ask spread	36.00%	84.00%	38.00%	32.00%	62.00%	36.00%
Days to cover	30.00%	80.00%	40.00%	16.00%	60.00%	40.00%
Dollar short interest	32.00%	82.00%	40.00%	24.00%	64.00%	40.00%
Forecast dispersion	6.12%	46.94%	26.53%	2.04%	0.00%	22.45%
Institutional ownership	6.00%	40.00%	26.00%	8.00%	4.00%	24.00%
Liquidity beta	26.53%	71.43%	42.86%	26.53%	57.14%	42.86%
Momentum	28.57%	69.39%	30.61%	30.61%	61.22%	32.65%
Share turnover	24.00%	70.00%	34.00%	28.00%	50.00%	36.00%
Short interest	28.00%	82.00%	44.00%	24.00%	64.00%	40.00%
Short-term reversal (1)	22.45%	61.22%	42.86%	20.41%	61.22%	42.86%
Short-term reversal (2)	40.00%	74.00%	32.00%	44.00%	74.00%	36.00%
Volatility	12.00%	56.00%	40.00%	26.00%	60.00%	34.00%

Table 2.15 continued

Panel B.2: Value-weighted portfolios

Hard-to-short measure	Without controlling for Fama and French (1993) factors			After controlling for Fama and French (1993) factors		
	Long leg	Short leg	Long-Short	Long leg	Short leg	Long-Short
Analyst coverage	10.20%	55.10%	22.45%	8.16%	40.82%	34.69%
Average rank	14.00%	42.00%	20.00%	12.00%	48.00%	28.00%
Book-to-market ratio	8.16%	44.90%	30.61%	14.29%	44.90%	28.57%
Cash flow-to-average assets	14.00%	36.00%	24.00%	18.00%	36.00%	22.00%
Corwin-Schultz bid-ask spread	14.00%	64.00%	34.00%	20.00%	62.00%	42.00%
Days to cover	20.00%	66.00%	22.00%	20.00%	58.00%	32.00%
Dollar short interest	28.00%	74.00%	32.00%	18.00%	60.00%	34.00%
Forecast dispersion	10.20%	26.53%	16.33%	10.20%	12.24%	26.53%
Institutional ownership	8.00%	28.00%	16.00%	8.00%	8.00%	24.00%
Liquidity beta	16.33%	55.10%	26.53%	16.33%	46.94%	30.61%
Momentum	12.24%	48.98%	20.41%	16.33%	55.10%	28.57%
Share turnover	8.00%	40.00%	20.00%	10.00%	34.00%	28.00%
Short interest	20.00%	66.00%	30.00%	18.00%	58.00%	30.00%
Short-term reversal (1)	16.33%	46.94%	22.45%	12.24%	61.22%	38.78%
Short-term reversal (2)	14.00%	42.00%	22.00%	14.00%	48.00%	32.00%
Volatility	14.00%	44.00%	22.00%	14.00%	40.00%	22.00%

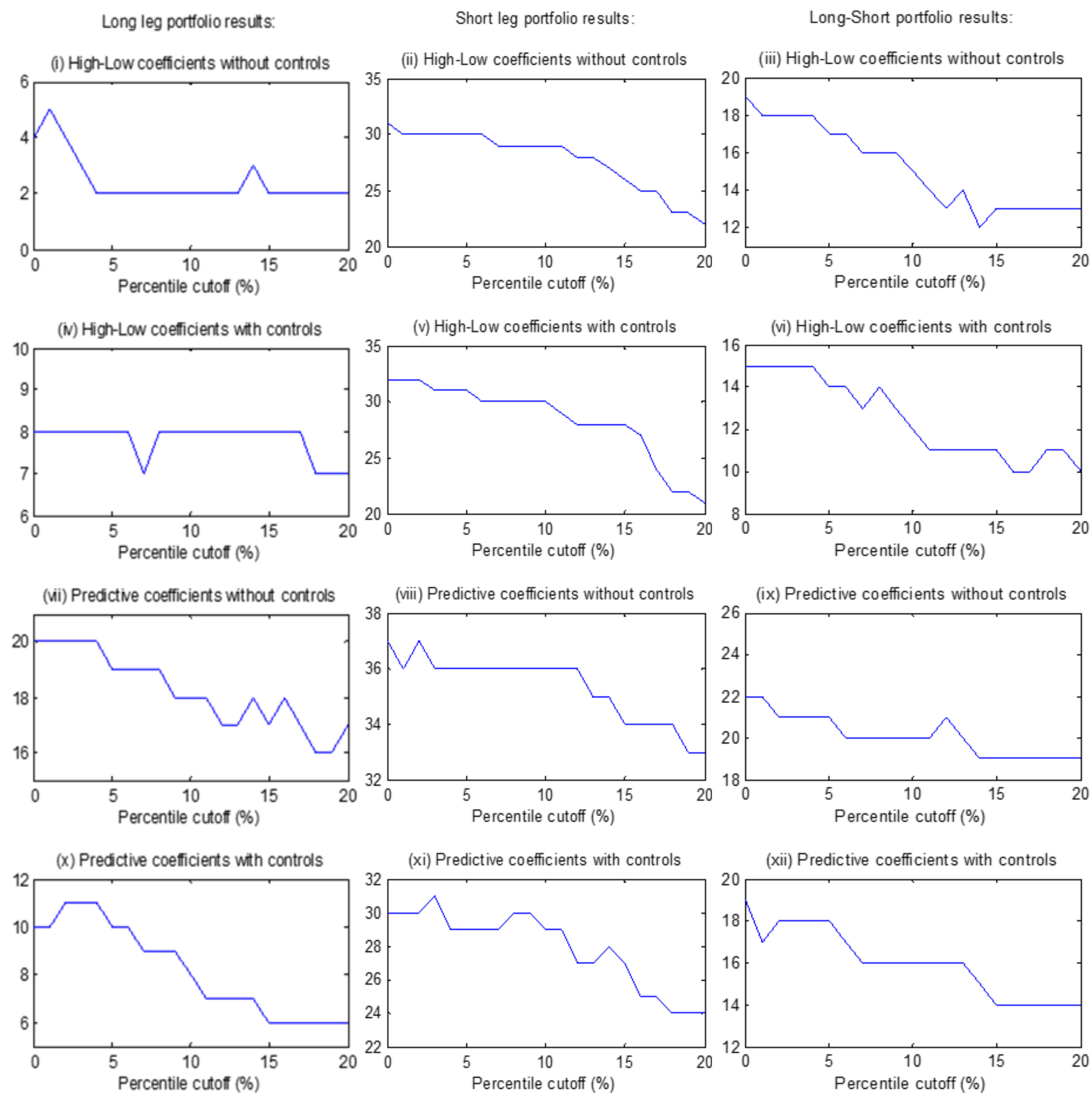


Figure 2.1 Number of statistically significant coefficients after excluding hard-to-short securities measured using average rank. This figure plots the number of trading strategies that have statistically significant coefficients after excluding firms with high average rank. Average rank is calculated by ranking firms on each of the 32 hard-to-short measures and then calculating the average rank across all measures. First, using all 50 trading strategies, I determine the number of statistically significant high-low and predictive regression coefficients without excluding any firms. Next, this procedure is repeated for portfolios formed after excluding firms in the highest percentile of average rank. These steps are repeated for percentile cutoffs ranging from 2% to 20%, incremented by 1%. Going across the columns, we report results for the long leg, short leg, and long-short portfolios. The first 2 rows plot the number of statistically significant high-low coefficients without and with controlling for the Fama and French (1993) factors, respectively. The last 2 rows plot the fraction of statistically significant predictive regression coefficients without and with controlling for the Fama and French (1993) factors. Trading strategy returns are calculated using value-weighted portfolios.

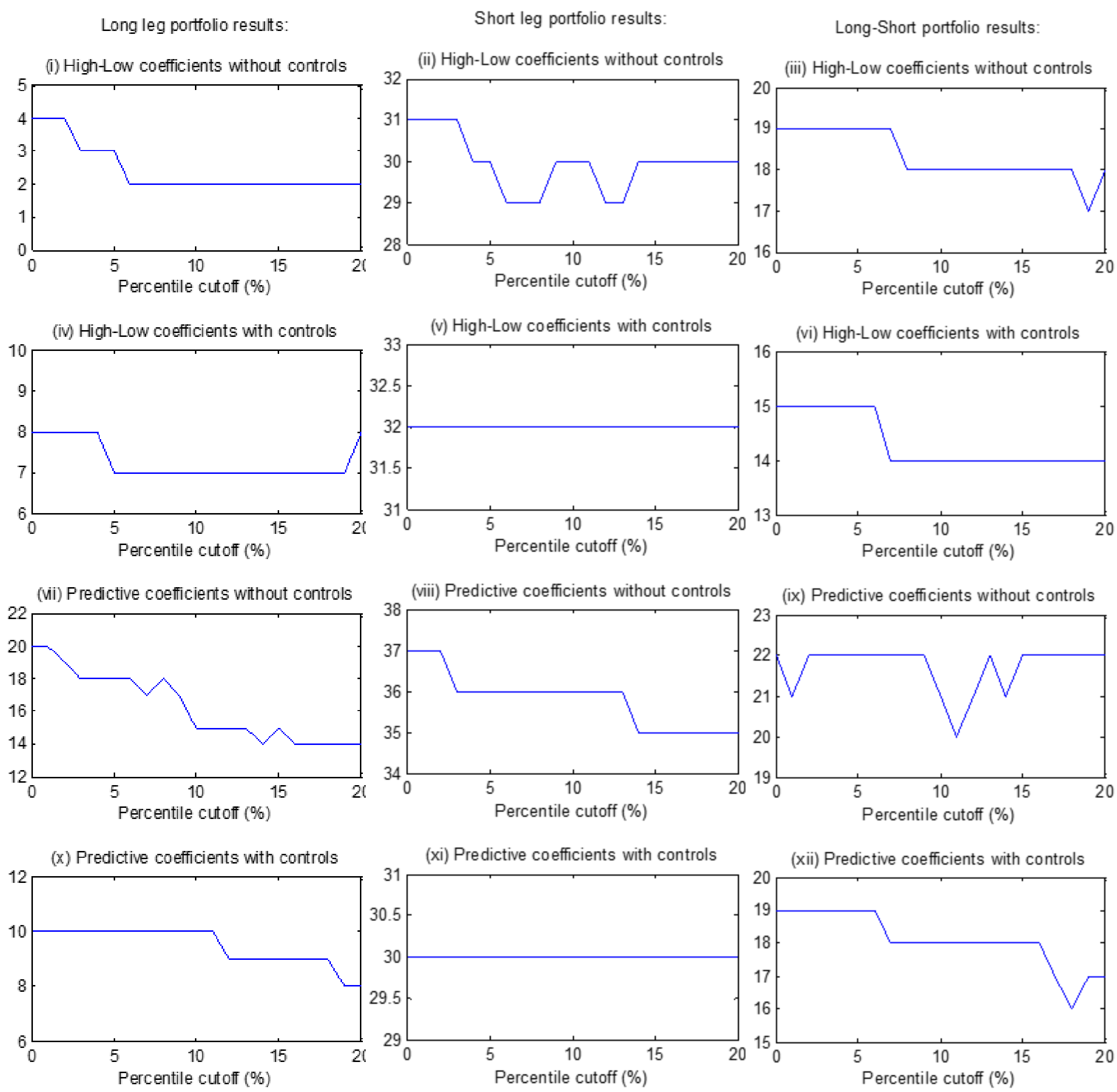


Figure 2.2 Number of statistically significant coefficients after excluding hard-to-short securities measured using firm size. This figure plots the number of trading strategies that have statistically significant coefficients after excluding firms with low market capitalization (small firms). First, using all 50 trading strategies, I determine the number of statistically significant high-low and predictive regression coefficients without excluding any firms. Next, this procedure is repeated for portfolios formed after excluding firms in the lowest percentile of firm size. These steps are repeated for percentile cutoffs ranging from 2% to 20%, incremented by 1%. Going across the columns, we report results for the long leg, short leg, and long-short portfolios. The first 2 rows plot the number of statistically significant high-low coefficients without and with controlling for the Fama and French (1993) factors, respectively. The last 2 rows plot the number of statistically significant predictive regression coefficients without and with controlling for the Fama and French (1993) factors. Trading strategy returns are calculated using value-weighted portfolios.

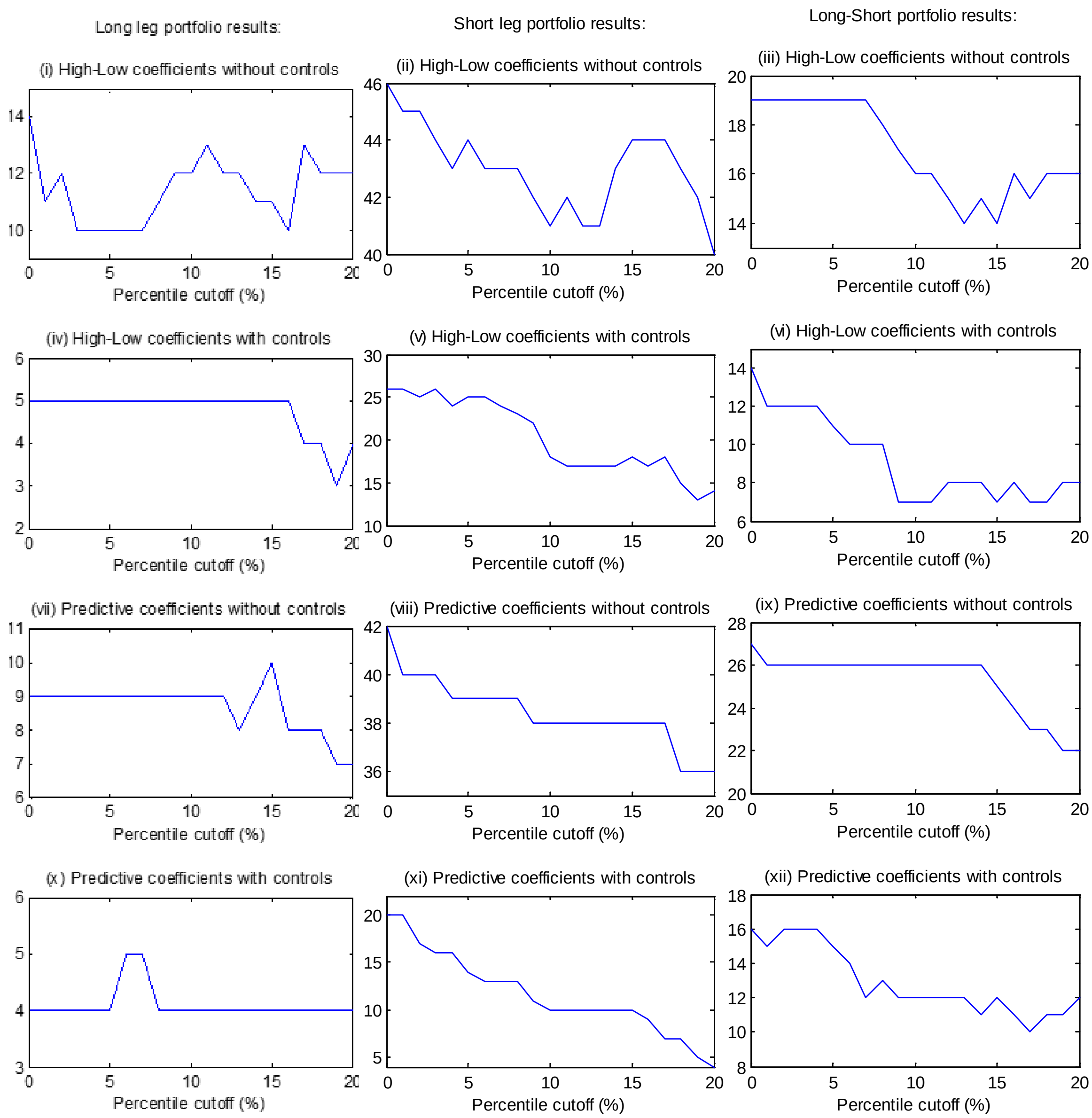


Figure 2.3 Number of statistically significant coefficients after excluding hard-to-short securities measured using institutional ownership. This figure plots the number of trading strategies that have statistically significant coefficients after excluding firms with low institutional ownership. First, using all 50 trading strategies, I determine the number of statistically significant high-low and predictive regression coefficients without excluding any firms with low institutional ownership. Next, this procedure is repeated for portfolios formed after excluding firms in the lowest percentile of institutional ownership. These steps are repeated for percentile cutoffs ranging from 2% to 20%, incremented by 1%. Going across the columns, we report results for the long leg, short leg, and long-short portfolios. The first 2 rows plot the number of statistically significant high-low coefficients without and with controlling for the Fama and French (1993) factors, respectively. The last 2 rows plot the number of statistically significant predictive regression coefficients without and with controlling for the Fama and French (1993) factors. Trading strategy returns are calculated using value-weighted portfolios.

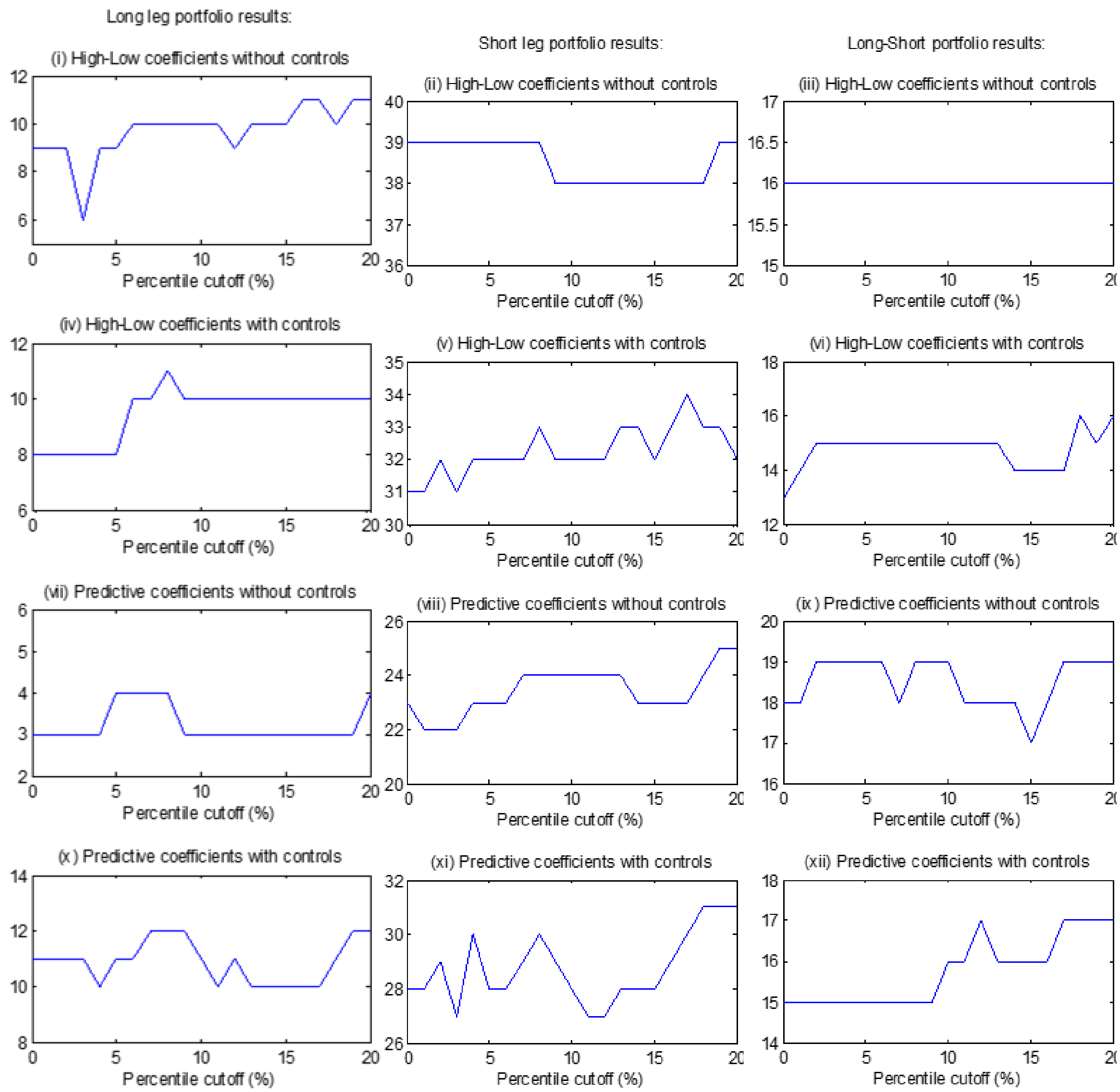


Figure 2.4 Number of statistically significant coefficients after excluding hard-to-short securities measured using short interest. This figure plots the number of trading strategies that have statistically significant coefficients after excluding firms with high short interest. First, using all 50 trading strategies, I determine the number of statistically significant high-low and predictive regression coefficients without excluding any firms with high short interest. Next, this procedure is repeated for portfolios formed after excluding firms in the highest percentile of short interest. These steps are repeated for percentile cutoffs ranging from 2% to 20%, incremented by 1%. Going across the columns, we report results for the long leg, short leg, and long-short portfolios. The first 2 rows plot the number of statistically significant high-low coefficients without and with controlling for the Fama and French (1993) factors, respectively. The last 2 rows plot the number of statistically significant predictive regression coefficients without and with controlling for the Fama and French (1993) factors. Trading strategy returns are calculated using value-weighted portfolios.

CHAPTER 3

INSTITUTIONAL TRADING MOMENTUM AND MISPRICING

Since the early 1980s, institutional ownership has been increasing over time (see Gompers and Metrick (2001)). Thus, financial institutions may play an important role in setting equity prices. This raises the concern that if financial institutions were to trade in the same direction, prices could be pushed away from fundamentals, thereby creating mispricing in the market. However, the general consensus in the literature is that financial institutions are beneficial to the market, in that they push prices towards, rather than away from, fundamentals. Wermers (1999) finds a positive relation between mutual fund demand and short-term returns. Using changes in institutional ownership as a proxy for institutional demand, Nofsinger and Sias (1999) also find a positive relation between institutional demand and short-term returns. Recently, Dasgupta et al. (2011) suggest that the reason prior studies have found a positive relation between institutional demand and short-term returns could be that the prior studies condition upon current institutional demand and not on institutional demand over multiple quarters. In contrast, the Dasgupta et al. (2011) findings show that firms bought or sold over consecutive quarters eventually have a reversal in returns over the long-run.

Unlike the results of previous studies, by using a novel measure of institutional demand, I find that financial institutions not only push prices away from fundamentals, but they also create substantial mispricing. I measure institutional demand using abnormal institutional ownership, the residual ownership that remains after de-trending institutional ownership with the Hodrick-Prescott (1997) filter.

First, I investigate how the level of abnormal institutional ownership has changed over time and find that abnormal institutional ownership was particularly high prior to the financial crisis of 2007-2009. After testing abnormal institutional ownership against other institutional ownership variables, I find that it contains information not captured by these other ownership variables. Next, using Fama and MacBeth (1973) regressions, I regress annual returns on abnormal institutional ownership, finding a strong negative relation between abnormal institutional ownership and annual returns. This result remains relatively unchanged even after controlling for other financial variables that have been shown to predict stock returns.

Theoretically, based on the argument presented in Lakonishok et al. (1992), if financial institutions exert pressure on equity securities and push their valuations away from fundamentals, long positions should be taken in securities with low abnormal institutional ownership and short positions should be taken in securities with high abnormal institutional ownership. To test this claim, I form portfolios by sorting firms based on abnormal institutional ownership. I find a strong mean-reversion in both abnormal institutional ownership and in returns. Securities in the high abnormal institutional ownership portfolio experience a large run-up in both abnormal and raw institutional ownership prior to the portfolio formation date, and a correspondingly large decline in abnormal and raw institutional ownership after the portfolio formation date. The opposite result is found for securities in the low abnormal institutional ownership portfolio. Instead, these securities experience a large decline in abnormal and raw institutional ownership prior to portfolio formation, followed by a quick increase in abnormal and raw institutional ownership after the portfolio formation date. A similar result is found with the returns of the low-high abnormal institutional ownership portfolio. This portfolio experiences negative returns prior to portfolio formation and positive returns after portfolio formation.

The evidence indicates that the aggregate trades of financial institutions exert considerable price pressure on securities. Prior to formation, the net order imbalance between buys and sells of the low-high abnormal institutional ownership portfolio reaches close to -$300 million. Then, following formation this order imbalance quickly reverts back to 0 over the following 4 quarters, and eventually reaches +$100 million 8 quarters after the formation date. The large order imbalance appears to be driven by mutual funds and other financial institutions that are not banks and insurance companies. The order imbalance of banks and insurance companies is approximately -$60 million, while the order imbalance of mutual funds and other financial institutions is approximately -$240 million. This suggests that mutual funds and hedge funds are responsible for pushing prices away from fundamentals.

The trades of financial institutions result in wide fluctuations in the relative valuation of the high abnormal institutional ownership. As financial institutions increase their ownership of the high abnormal institutional ownership portfolio, the average book-to-market ratio of this portfolio drops from 0.73 to 0.52, then as financial institutions decrease their holdings of this portfolio, the average book-to-market ratio increases from 0.52 to 1.15.

Further evidence indicates that financial institutions push prices away from fundamentals. Prior to the sorting date on abnormal institutional ownership, the high and low abnormal institutional ownership portfolio have similar returns. However, as the order imbalance between these extreme portfolio increases, the high abnormal institutional ownership portfolio consistently experiences much larger returns than the low abnormal institutional ownership portfolio over the subsequent months up until the formation date. Then following the formation date, there is a reversal, and the high abnormal institutional ownership portfolio experiences much smaller returns than the low abnormal institutional ownership portfolio. This reversal in returns results in the low and high abnormal institutional ownership portfolios having the same cumulative return 15 months after formation. From 36 months to 3 months prior to formation, the low-high abnormal institutional ownership portfolio experiences a cumulative return of -35%. Then, there is a reversal, and the low-high abnormal institutional ownership portfolio experiences positive returns over the following 18 months, resulting in a net cumulative return of 0% 15 months after the sorting date.

I find that a strategy that purchases the extremely low institutional ownership portfolio and sells the extremely high institutional ownership portfolio earns a positive and statistically significant return. The average monthly return for this strategy using equally-weighted portfolios is 2.75%, while the average monthly return using value-weighted portfolios is 1.17%. This result seems likely due to mispricing, since after controlling for the Fama and French (1993) factors, the average monthly alpha is 2.79% for the strategy formed using equally-weighted portfolios and the average monthly alpha is 1.21% using value-weighted portfolios.

The negative relation between abnormal institutional ownership and returns is inversely related to firm size. Using Fama and MacBeth (1973) regressions, the average abnormal institutional ownership coefficient is between -0.15 and -0.20 for small firms, but between -0.02 and -0.04 for large firms. A similar result is found using portfolios formed on both abnormal institutional ownership and firm size. Within the smallest tertile, the average equally-weighted return of the low-high abnormal institutional ownership portfolio is 3.48% per month, while within the largest tertile, the average equally-weighted return is 0.77% per month. Similar results are found using value-weighted portfolios and these estimates remain relatively unchanged after controlling for the Fama and French (1993) factors.

Consistent with Amihud's (2002) suggestion that illiquid firms should be more sensitive to large trades, i.e., institutional demand, I find that illiquid securities are more sensitive to institutional demand than liquid securities. After allocating firms to 3 illiquidity portfolios and 10 abnormal institutional ownership portfolios, I find that within the most illiquid tertile, the low-high abnormal institutional ownership portfolio earns an average monthly equally-weighted return of 3.37% and an average monthly value-weighted return of 2.53%. On the other hand, within the least illiquid portfolio, the low-high portfolio earns an average equally-weighted return of 1.32% and an average value-weighted return of 0.66%. A similar result is obtained after controlling for the Fama and French (1993) factors.

I test to determine whether the negative relation between institutional demand and returns was stronger in one subperiod over another. One would expect that if financial institutions exert a greater effect on prices while holding a large fraction of outstanding shares, the low-high abnormal institutional ownership strategy would earn a higher return in the later part of the sample, when institutional ownership was highest. This is exactly what I find. In the 1980s, the average return of the low-high portfolio earned an average monthly equally-weighted return of 1.87%. In contrast, this same portfolio had an average equally-weighted return of 3.55% in the 1990s and an average equally-weighted return of 2.89% in the 2000s. Thus, the negative relation between institutional demand and returns is strongest when financial institutions play a larger role in the market.

I investigate whether my results can be extended to subgroups of financial institutions. Following the methodology of Lewellen (2011), I classify each financial institution as a bank, insurance company, mutual fund, or other financial institution. I then construct abnormal ownership for each type of financial institution calculated using the aggregate holdings of each institution type. Then, portfolio returns are calculated for low-high abnormal ownership portfolios that are formed using abnormal bank ownership, insurance ownership, mutual fund ownership, and other financial institution ownership. For each subgroup of financial institutions, I find the same mean-reversion pattern in ownership and returns. The strategy using abnormal mutual fund ownership generates the largest average low-high portfolio return, while the strategy using abnormal insurance ownership generates the smallest average low-portfolio return. Further, the largest reversion in returns is found using abnormal mutual fund ownership. Consistent with the earlier results found using abnormal institutional ownership, I find that the low-high abnormal mutual fund ownership portfolio experiences large negative returns prior to the sorting date and large positive returns after the sorting date. Unlike the case using abnormal institutional ownership, I find that the reversion in returns related to abnormal mutual fund ownership is almost exclusively due to the trades of mutual funds. At the point of reversal in abnormal mutual fund ownership, the order imbalance of mutual funds is around -$180 million, while the order imbalance of all other financial institutions is around +$5 million. This suggests that the trades of mutual funds, if not balanced by the trades of other financial institutions, can create substantial mispricing in the market place.

Finally, I test the robustness of my results using residual ownership measures constructed by regressing each ownership series on a constant and a linear trend term. Using residual ownership, I find virtually the same results as when using abnormal ownership constructed using the Hodrick and Prescott (1997) filter.

The reason I find a negative relation between institutional demand and short-term returns is the use of de-trended institutional ownership as the measure of institutional demand. There are a number of advantages to this measure, relative to the measures traditionally used in the literature. First, de-trended institutional ownership captures the aggregate effect of the trades of all financial institutions, whereas some of the other measures capture only the actions of a subgroup of financial institutions. Consider the case of a single mutual selling a large block of stock to 10 different mutual funds. Under my measure, the level of institutional ownership would not change. However, a measure such as the Lakonishok et al. (1992) measure would conclude that mutual funds were net buyers, despite the lack of change in the overall level of institutional ownership. Additionally, our measure remains unchanged when the trades of one group of financial institutions, such as mutual funds, is offset by another group of financial institutions, such as insurance companies.

Another advantage of this measure is that it captures both the magnitude of changes in institutional ownership as well as the direction of those changes. Measures that count only the number of buyers versus sellers do not take into consideration the magnitude of those transactions. For example, fixing the number of buyers and sellers, one could discover that 1 set of trades moves institutional ownership from 1% to 20% while another moves institutional ownership from 1% to only 1.1%. De-trended institutional ownership is able to distinguish between these 2 cases.

De-trended institutional ownership is most closely related to the Dasgupta et al. (2011) institutional persistence measure and the change in institutional ownership measure used in Nofsinger and Sias (1999). The institutional persistence (henceforth referred to as either institutional persistence or persistence) measure counts the number of consecutive quarters in which a security was purchased or sold in net. In this regard, Dasgupta et al. (2011) capture the trend in institutional ownership over 3-5 quarters. However, they neither capture the magnitude of the change in ownership over those quarters nor take into consideration trends lasting longer than 5 quarters. Moreover, the change in institutional ownership measures the change in ownership from one quarter to the next but does not take into consideration changes in ownership over multiple quarters or trends in ownership. Alternatively, abnormal institutional ownership not only measures the net effect on ownership over multiple quarters, but it also measures any sudden changes in ownership. Thus, this measure is the best of both worlds.

A further advantage of this measure relative to other measures is its ability to control for trends in ownership. It allows me to select stocks at the exact moment their trend switches direction, whereas other measures may select stocks in the middle of a trend. Furthermore, this measure controls for different stocks having different average levels of ownership. One would think that a stock whose level of institutional ownership changes from 10% to 20% would be different from a stock whose level of institutional ownership changes from 50% to 60%.

My work is most closely related to the literature studying institutional demand (herding) and returns. Generally, this literature finds a positive relation between institutional demand and short-term returns. Lakonishok et al. (1992) create a new measure of institutional demand, the number of funds that are net buyers of a security, and then test whether these funds push prices away from or towards fundamentals. Their evidence seems to indicate that for the most part, financial institutions do not push prices away from fundamentals. In a related study, Wermers (1999) investigates the effect of mutual fund demand on returns, finding that the stocks bought by mutual funds tend to have positive subsequent returns, and stocks sold by mutual funds tend to have negative subsequent returns. This evidence indicates that mutual funds push prices towards fundamentals. Nofsinger and Sias (1999) investigate the relation between institutional demand and returns, using changes in institutional ownership as the measure of institutional demand. They present evidence of a continuation in prices in the short-term. Stocks with a large decrease in institutional ownership experience a negative return in the following year while stocks with a large increase in institutional ownership experience a positive return in the following year. My research contributes to this literature by presenting strong evidence of a negative relation between institutional demand and short-term returns.

In more recent work, Dasgupta et al. (2011) and Gutierrez and Kelley (2009) investigate the relation between institutional demand and returns after 1 year. They discover that there is a reversal in returns in the long-term. Interestingly, Gutierrez and Kelley also find a positive relation between institutional demand and short-term returns using the Lakonishok et al. (1992) herding measure, and also present some evidence of a negative relation using changes in institutional ownership. My results expand on these prior papers by using abnormal institutional ownership. I present evidence of a strong mean-reversion in both ownership and returns when institutional ownership is abnormally high or low.

My work is also related to the literature using the Hodrick-Prescott filter (1997) to remove trends from financial variables. Typically, the Hodrick-Prescott filter is used to remove the trend in economic output variables such as Gross Domestic Product and Gross National Product (see Braun and Larrain (2005) and Hodrick and Prescott (1997)). Other scholars have used the Hodrick-Prescott filter to de-trend other financial variables. Naes et al. (2011) use the Hodrick-Prescott (1997) filter to de-trend market illiquidity measured using the Amihud (2002) illiquidity measure and Campello and Graham (2013) used the Hodrick-Prescott (1997) filter to de-trend accounting ratios such as the price-to-earnings ratio and the cash flow to assets ratio. My research contributes to this literature by showing that the Hodrick-Prescott (1997) filter can be applied to institutional ownership as well.

The remainder of this paper is organized as follows: section 3.1 discusses the data and methodology, section 3.2 presents results indicating that financial institutions are pushing prices away from fundamentals, and section 3.3 concludes.

3.1 Data and Methodology

Data are obtained from a number of different sources. I obtain stock returns and other stock market data from the CRSP database and accounting data reported by firms from the COMPUSTAT database. Data necessary to construct institutional ownership and other related variables are obtained from the Thomson-Reuters Institutional Holdings (13F) database. Each quarter, financial institutions with more than $100 million in assets under management are required to report to the SEC their positions in equity securities as outlined in the Securities Exchange Act of 1934.[9] In this study I use institutional holdings data from March 1980 until December 2010. Institutional ownership is defined as the percentage of a firm's shares outstanding that is held by financial institutions. I also obtain mutual fund holdings from the Thomson-Reuters mutual fund holdings database.

I use shares outstanding from the CRSP database when constructing this variable. Delisting returns are controlled for following the methodology used in Bulsiewicz (2013). In all of my future analyses, I use only nonfinancial, nonutility firms with share price between \$5 and \$1,000, inclusive, as of the formation date.

Previously, Gompers, and Metrick (2001) documented that institutional ownership has been increasing over time. I am able to confirm this result in the sample period (1980-2010). From March 1980 until December 2010, the average equally-weighted institutional ownership increased from 12.7% to 55.7%, while the average value-weighted institutional ownership increased from 33.6% to 71.3%. The results for equally-weighted portfolios are reported in Figure 3.1.[10] In constructing these 2 time-series, I use all common shares (share codes equal to 10 or 11) that are traded in the United States.

I also calculate bank ownership, insurance ownership, mutual fund ownership, and other financial institutions ownership. I calculate mutual fund ownership by aggregating across all mutual funds in the Thomson Reuters mutual fund database. Bank ownership, insurance ownership, and other financial institutions ownership is calculated using the

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[9] More information on 13F institutional ownership filings is available at http://www.sec.gov/divisions/investment/13ffaq.htm

[10] For brevity, some results are omitted if they are similar to results already shown in a table or figure.

methodology used in Lewellen (2011). I classify all firms in the Thomson Reuters institutional ownership database as a bank, insurance company, or all other institutions. I then aggregate the holdings of each institution type. Other financial institutions ownership is calculated by subtracting mutual fund ownership (from the mutual fund database) from the all other financial institutions ownership.

The time series of bank, insurance, and other ownership is plotted in Figure 3.1. From this figure we can see the trend in institutional ownership is due to a large increase in mutual fund and other financial institutions' ownership. The ownership of banks and insurance companies has been fairly flat over time.

While previous studies have generally found a positive relation between institutional trading and short-term stock returns, none of these studies have explicitly controlled for trends in institutional ownership. One measure used in these studies is the Lakonishok et al. (1992) herding measure which measures the number of mutual funds buying a certain security. Wermers (1999) uses the Lakonishok et al. (1992) herding measure to study whether mutual fund herding, mutual funds that all trade in the same direction, push prices towards or away from fundamentals and finds evidence that mutual funds push prices towards fundamentals. The Lakonishok measure takes into account whether mutual funds are on average buyers or sellers in a given quarter, but it does not take into account trends in institutional ownership. Another institutional demand measure used in the literature is the proportion of institutions that increase their holdings in a security. Using the proportion of institutions increasing their demand for a security, Sias (2004) finds a positive relation between institutional demand and returns over the following year. While the proportion of institutions increasing their holdings in a security measures institutional demand, it does not take into account trends in institutional ownership. Similarly, some studies use the change in institutional ownership to assess whether there is a positive relation between institution trading and short-term returns (see for example Nofsinger and Sias (1999)).

The change in institutional ownership controls for the current change in ownership, but it does not take into account how ownership changed over multiple quarters. Recently, Dasgupta et al. (2011) measured institutional demand by counting the number of consecutive quarters that financial institutions either increased or decreased their holdings in a security. They provide evidence that there is a reversal in returns in the long-term following a period where a security is bought or sold over many quarters and also provide some evidence that returns may reverse sooner than 1 year in the future.

Unlike the prior literature, I explicitly control for trends in institutional ownership. For each equity security I de-trend each equity security's full time-series of institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. After de-trending each security's institutional ownership I define abnormal institutional ownership as the residual ownership remaining after removing the trend (slope and level) from institutional ownership.

Figure 3.2 plots the time-series of abnormal institutional ownership for the whole market by equally weighting each security. Looking at Figure 3.3, there appear to be cycles in abnormal institutional ownership, i.e., there are periods where institutional ownership is increasing and periods where institutional ownership is decreasing. Interestingly, prior to the financial crisis, there was a large increase in abnormal institutional ownership and subsequently there was a large decrease in abnormal institutional ownership. I find similar results using value-weighted abnormal institutional ownership, except I also find a large spike in abnormal institutional ownership during the Tech bubble and 2001 recession.

3.2 Results

After calculating abnormal institutional ownership, the first order of business is to determine the relation between abnormal institutional ownership and other institutional ownership measures. For each security, I calculate a total of 7 institutional ownership measures: abnormal institutional ownership, change in abnormal institutional ownership, change in institutional ownership, institutional ownership, institutional persistence, mutual fund herding, and residual institutional ownership. Change in abnormal institutional ownership is defined as the 1 quarter change in abnormal institutional ownership and the change in institutional ownership is defined as the 1 quarter change in raw institutional ownership. Mutual fund herding is calculated using the Lakonishok et al. (1992) measure following the methodology of Wermers (1999). The Lakonishok et al. (1992) measure is defined as $HM_{i,t} = |p_{i,t} - E[p_{i,t}]| - AF_{i,t}$ where $p_{i,t}$ is the proportion of buying and selling mutual funds that increase their holdings of stock *i* in quarter *t*. and $AF_{i,t}$ is an adjustment factor which takes into account that the expected value of $|p_{i,t} - E[p_{i,t}]|$ is greater than 0 under the null of no herding. The adjustment factor is defined as $AF(i) = E|p_{i,t} - E[p_{i,t}]|$. Following Dasgupta et al. (2011) I define institutional persistence as the number of quarters that institutional ownership was bought over the most recent 3 quarters, inclusive of the current quarter. Nagel residual institutional ownership is as defined in Nagel (2005), who defines residual institutional ownership as the residual from the regression equation:

$$logit(INST) = \alpha + \beta_1 LOGSZ_{i,t} + \beta_2 (LOGSZ_{i,t})^2 + e_{i,t} \qquad (16)$$

where INST is institutional ownership, $\text{logit(INST)} = \log(\frac{INST}{1-INST})$, $LOGSZ_{i,t}$ is the log of firm size, and $(LOGSZ_{i,t})^2$ is the log of firm size squared. Nagel uses residual institutional ownership to control for institutional ownership that is related to firm size. To test the robustness of the use of abnormal institutional ownership, I also calculate residual institutional ownership. Residual institutional ownership is defined as the residual from the regression of firm-level institutional ownership on a constant and a time trend term.[11]

As argued in Dasgupta et al. (2011), I standardize each of the 9 institutional ownership variables by the quarterly cross-sectional mean and standard deviation in order to be able to interpret the coefficients from any future regressions. Prior to running any regressions, I calculate the correlations between these 9 measures. These correlations are reported in Table 3.1.

Abnormal institutional ownership is moderately correlated with the other institutional ownership measures used in prior studies. Of these measures, abnormal institutional ownership has the highest correlation with the 1 quarter change in institutional ownership and is negatively correlated with mutual fund herding. Abnormal institutional ownership is also moderately correlated with the 1 quarter change in abnormal institutional ownership and highly correlated with residual institutional ownership. The correlation between abnormal institutional ownership and residual institutional ownership is 82%.

I also calculate abnormal ownership for the 4 subgroups of financial institutions using bank ownership, insurance ownership, mutual fund ownership, and other ownership. I define abnormal ownership using these 4 series as abnormal bank ownership, abnormal

[11] In this paper, I will refer to the residual ownership from Nagel (2005) as Nagel (2005) residual ownership and the residual ownership from the regression of ownership on a constant and a time trend term as residual ownership.

insurance ownership, abnormal mutual fund ownership, and abnormal other ownership. Table 3.2 presents the correlation matrix between abnormal institutional ownership and the 4 other abnormal ownership measures. Abnormal institutional ownership has a relatively high correlation of 73% with abnormal other ownership and is not highly correlated with abnormal bank, insurance, and mutual fund ownership. In addition, the correlation between the abnormal ownership of each subgroup is low.

3.2.1 Fama MacBeth Tests

While abnormal institutional ownership is related to the other measures of institutional ownership, it is not yet clear if it contains additional information not captured by other institutional ownership variables. To test whether abnormal institutional ownership contains information not contained in the other measures, I run Fama-MacBeth (1973) regressions of future 1 year buy and hold returns on each of the 9 institutional ownership variables. Specifically, I regress the buy and hold return from July of year *t* until June of year *t+1* on each of the institutional ownership measures in June of year *t*. The coefficient estimates for each of the variables are presented in Table 3.3. Panel A of Table 3.3 shows the results for all firms, while Panels B, C, and D show the results for small, medium, and large market capitalization firms. I define small firms as firms with market capitalization less than the 30^{th} percentile, medium firms as firms with market capitalization between the 30^{th} and 70^{th} percentile, and large firms as firms with market capitalization greater than the 70^{th} percentile. This definition of firm size was previously used in Cooper et al. (2008).

If financial institutions push prices away from fundamentals, then there should be a negative relation between abnormal institutional ownership and short-term returns. This is exactly what I find. Overall, there is a strong negative relation between abnormal institutional ownership and short-term returns and a negative, but weaker, relation between the change in abnormal institutional ownership and short-term returns. On the other hand, consistent with the prior literature, I find an insignificant relation between short-term returns and change in institutional ownership, institutional ownership, mutual fund herding, or persistence. Furthermore, I find a positive relation between Nagel (2005) residual institutional ownership and short-term returns. I also find that abnormal institutional ownership produces a much higher average adjusted *r*-squared than any of the other measures. These results indicate that abnormal institutional ownership contains new information not present in the other measures.

Comparing the results using abnormal institutional ownership or residual institutional ownership, we can see that there is a negative relation between these measures and short-term returns. In unreported results, I find that the results reported in this paper are only slightly weaker to the use of residual institutional ownership in the place of abnormal institutional ownership, so for brevity I focus only on the results obtained using abnormal institutional ownership.

Next, I test whether the negative relation between abnormal institutional ownership and short-term returns is present in all 3 size groups. The negative relation between institutional ownership and short-term returns increases in strength as we move from large firms to small firms. The estimated coefficients are -0.0264, -0.0783, and -0.1511 for large, medium, and small firms, respectively. Furthermore, the average adjusted *r*-squared from these regressions is highest for small firms and lowest for large firms. These results are consistent with Amihud (2002), which suggests that the securities of small firms are more illiquid and more sensitive to large trades. If small firms are more sensitive to institutional demand than large firms, then this would explain why there is a stronger negative relation between abnormal institutional ownership and short-term returns.

Given that abnormal institutional ownership has a fairly high correlation with the change in abnormal institutional ownership and change in institutional ownership variables but has a larger effect on future returns than these other variables, I do not include these 2 other institutional ownership variables in future Fama-MacBeth (1973) tests. I also exclude institutional ownership as an explanatory variable since it is highly correlated with Nagel (2005) residual institutional ownership. While the previous results showed that abnormal institutional ownership contains information not contained in other institutional ownership variables, abnormal institutional ownership could be capturing information in other financial variables. I consider a total of 14 other financial variables: accruals, asset growth, book-to-market ratio, Daniel and Titman Composite issuances, firm size, gross profitability, idiosyncratic risk, investments-to-assets, momentum, net stock issuances, O-score, return on assets return on equity, and share turnover. A more detailed description of these variables is given in Appendix C.

Prior to running any Fama-MacBeth (1973) regressions, I calculate the correlation between abnormal institutional ownership and the 17 other financial variables. Each variable is standardized by its quarterly cross-sectional mean and standard deviation. I exclude firms with low prices (less than $5), high prices (greater than $1,000), financial firms (SIC codes between 6000 and 6999), and utilities (SIC codes between 4900 and 4999). These correlations are given in Table 3.4. Abnormal institutional ownership has the highest correlation with the 2 other institutional ownership variables, persistence and

Nagel (2005) residual institutional ownership. Further, the correlations between abnormal institutional ownership and the other financial variables have an absolute value less than 10%.

I perform Fama MacBeth (1973) regressions of annual July of year *t* until June of year *t+1* returns on abnormal institutional ownership and other financial variables from June of year *t*. The average coefficient estimates and their corresponding *t*-statistics are reported in Table 3.5, with Panel A reporting the results for all firms, and Panels B, C, and D reporting the results for different size groups. I first estimate the relation between future returns and abnormal institutional ownership. From this regression I find a strong and highly significant negative relation between abnormal institutional ownership and returns. In regression Specification 2, I add the 3 institutional ownership variables: mutual fund herding, Nagel (2005) residual institutional ownership, and persistence. Even after adding these variables there is still a strong negative relation between abnormal institutional ownership and short-term returns. Further, the mutual fund herding coefficient is not statistically different and there is a positive relation between the other 2 institutional ownership variables and short-term returns. Next, I add Daniel and Titman (2006) composite issuances and return on assets as control variables. Again, there is a strong negative relation between abnormal institutional ownership and short-term returns. In regression Specification 4 I add gross profitability and share turnover, and in Specification 5 I include all 17 control variables. Consistent with the other 3 specifications, the relation between abnormal institutional ownership and short-term returns is relatively unchanged after including all of these control variables known to predict returns.

I repeat these 5 specifications for small, medium, and large firms. Small firms have a much stronger relation between returns and abnormal institutional ownership than the other 2 size groups. The average abnormal institutional ownership coefficient for small firms is approximately -0.185 for small firms, -0.097 for medium firms, and -0.028 for large firms. Thus, as firm size increases, the effect of abnormal institutional ownership on returns decreases. This is consistent with Amihud's (2002) suggestion that small firms are more sensitive to large trades. Furthermore, unlike the general result reported in the literature, these results suggest that financial institutions push prices away from rather than towards fundamentals.

3.2.2 Fama MacBeth Tests by Institution Subgroup

In this section, I investigate whether the results presented in the last section can be extended to subgroups of financial institutions. I run the 5 Fama-MacBeth (1973) regressions using abnormal bank, insurance, mutual fund, and other ownership. The estimated Fama-MacBeth coefficients are reported in Table 3.6, with Panels A, B, C, and D presenting the results using abnormal bank, insurance, mutual fund, and other ownership. For all 4 types of institutions there is a significant negative relation between their abnormal ownership and short-term returns. Out of the 4 types of institutions, the strongest results are found using abnormal mutual fund ownership and the weakest results are found using abnormal insurance ownership. Thus, all 4 institutions seem to exert an effect on returns, with banks and insurance companies exerting the least and mutual funds, hedge funds, and other institutions exerting the most.

3.2.3 Abnormal Institutional Ownership Portfolio Tests

To further examine the relation between institutional demand and returns, in June of each year from 1980 until 2010, I allocate firms into 10 decile portfolios using New York Stock Exchange (NYSE) breakpoints. I then calculate the average characteristics across all years for each of the 10 portfolios. I report these descriptive statistics in Table 3.7. From this table we can see that there is a wide dispersion in abnormal institutional ownership. The average abnormal institutional ownership in portfolio 1 is -0.0890 and in portfolio 10 is 0.1064. We can also see that firms with high abnormal institutional ownership have higher institutional ownership as well as Nagel (2005) residual institutional ownership. Firms with high abnormal institutional ownership have around 28% more of its shares held by financial institutions. Interestingly, firms with low abnormal institutional ownership have not been persistently sold. The Dasgupta et al. (2011) persistence measure takes a value of -3 if a stock has been sold over the prior 3 quarters, but here I am finding the average persistence for portfolio 1 is -0.06, which is close to 0. This implies that firms with low abnormal institutional ownership have been neither persistently bought nor sold, which suggests that financial institutions sell a large portion of their holdings in 1 quarter rather than selling small portions of their holdings over multiple quarters. Based on this, it does appear that abnormal institutional ownership is capturing institutional demand or alternatively institutional price pressure.

I find a different result for high abnormal institutional ownership firms. These firms have been persistently bought over at least the prior 2 quarters. The average persistence for high abnormal institutional ownership firms is 1.88. The average firm with low abnormal institutional ownership has a higher book-to-market ratio, smaller market capitalization, and lower return on equity than the average firm with high abnormal institutional ownership. However, these results could be due to financial institutions pushing the price of the low abnormal institutional ownership portfolio down and pushing up the price of the high abnormal institutional ownership portfolio. Additionally, firms with high abnormal institutional ownership have a higher return over the prior year as shown by the momentum variable.

3.2.3.1 Abnormal Institutional Ownership in Event Time

Next I investigate how abnormal institutional ownership changes prior to and after the allocation date. If financial institutions are driving prices away from fundamentals, then we would expect for there to be a spike in abnormal institutional ownership centered on the allocation quarter. This is exactly what I find. For each of the 10 abnormal institutional ownership portfolios I calculate the cross-sectional average abnormal institutional ownership for the 12 quarters before and after the allocation quarter. These values are plotted for each portfolio in Figure 3.3. For the high abnormal institutional ownership portfolio, we see that leading up to the allocation quarter abnormal institutional ownership increases rapidly from -0.028 to 0.130 at the end of the allocation quarter and then decreases rapidly to a level around -0.035.

I find the opposite result for the low abnormal institutional ownership portfolio. For the low abnormal institutional ownership portfolio, abnormal institutional ownership is around 0.02 prior to the allocation quarter, decreases to -0.11 at the end of the allocation quarter, and then proceeds to increase back to a level around 0.04. Thus, there is strong mean-reversion in abnormal institutional ownership. These results provide further support that institutions are pushing prices away from fundamentals. It seems inconsistent to think that financial institutions would be altering their ownership level if they thought these investments would yield a high return.

I also investigate how the level of abnormal institutional ownership changes around the sorting date for the low-high abnormal institutional ownership portfolio. For each of the 12 quarters surrounding the formation date, I calculate the difference in the average abnormal institutional ownership for the low-high portfolio. In Figure 3.4, I plot how abnormal institutional ownership changes around the sorting date for the low-high portfolio. From this figure we see that there is strong mean reversion in ownership. Prior to the sorting date, there is a much larger increase in abnormal institutional ownership for the high abnormal institutional ownership portfolio than there is a decrease in abnormal institutional ownership for the low abnormal institutional ownership portfolio. This results in the net abnormal ownership being negative prior to the sorting date. However, following the sorting date, this pattern reverses and the low ownership portfolio sees a larger increase in ownership while the high ownership portfolio sees the opposite change. This results in a large net increase in abnormal institutional ownership following the sorting date. Further, based on Figure 3.4, there appears to be escalation in the trades of financial institutions given that abnormal institutional ownership is concave and decreasing prior to the sorting date and increasing after the sorting date.

3.2.3.2 Institutional Ownership in Event Time

To provide further insight on the prior results, I also calculate the mean amount of institutional ownership for the 10 abnormal institutional portfolios for the 12 quarters surrounding the allocation date. The time-series of average institutional ownership for the low and high abnormal institutional ownership portfolios are plotted in Figure 3.5. Even when using raw institutional ownership, I still find strong mean-reversion. From 12 quarters prior to the allocation date to the allocation date, the average institutional ownership of the high abnormal institutional portfolio increases from average level of 38% to 62% on the allocation date. Then, after the allocation quarter, the average institutional ownership decreases to approximately 48%. The opposite result is found for the low abnormal institutional ownership portfolio. Prior to the allocation date, the average institutional ownership of the low abnormal institutional ownership portfolio decreases from around 47% to slightly less than 36%. After the allocation quarter, the average institutional ownership increases to a level close to 57%. Thus, I find a reversal in institutional ownership for both the low abnormal institutional ownership portfolio and the high abnormal institutional ownership portfolio.

3.2.3.3 Returns to Abnormal Institutional Ownership Strategy in Event Time

If institutional demand is pushing prices away from fundamentals, then this would suggest that a strategy that purchases low abnormal institutional ownership firms and sells high abnormal institutional ownership firms would be profitable. After forming 10 portfolios in June, for each portfolio I calculate the cross-sectional average return for the 36 months surrounding the allocation month. I also calculate the returns to strategies that sort stocks on each of the abnormal ownership subgroups. Figure 3.6 plots the cumulative average monthly return surrounding the formation month for the strategy that buys low abnormal institutional ownership firms and sells high abnormal institutional ownership firms as well as the low-high portfolios formed using abnormal bank, insurance, mutual fund, and other ownership. There is substantial mean-reversion in returns. Prior to the formation month, returns become increasingly negative. In total, the cumulative return to the low-high abnormal institutional ownership portfolio is -35% up to 3 months prior to the sorting date, then there is a large reversal and returns are positive for the next 20 months or so. By the 17th month after formation, the cumulative return is back to 0. In total, financial institutions appear to push prices away from fundamentals for 33 months and to push prices back towards fundamentals for 20 months. A similar pattern is found for each group of financial institutions. Specifically, strategies formed using abnormal bank, insurance, mutual fund, and other ownership all produce negative returns prior to the sorting date and positive returns following the sorting date. Overall, the strongest effect is found using abnormal ownership for all institutions, but each group of institutions appears to be creating mispricing. Out of the 4 types of institutions, the strategy using abnormal mutual fund ownership has the largest mean-reversion in returns, followed by the strategies using abnormal bank, other, and insurance ownership, in order of decreasing mean-reversion.

To further investigate whether institutions are creating mispricing, Figure 3.7 shows how $1 invested at the end of the 37th month prior to the sort date would change if it were invested in the low and high abnormal institutional ownership portfolios. From this figure, there appears to be mispricing, which based on the institutional ownership evidence, appears to be driven by the trades of financial institutions. Up to 27 months before the sort date, the value of $1 would have grown to about the same amount in both the low and high portfolios. However, after this date the high abnormal institutional ownership outperforms the low abnormal institutional ownership portfolio by an ever increasing margin up until around the sorting date.

At the peak, the $1 invested in the high portfolio would be worth almost 89 cents more than the $1 invested in the low abnormal institutional ownership portfolio. However, around the sorting date, this all changes since the value of $1 in the high portfolio converges back towards the value of the $1 invested in the low portfolio, and around the 15th month after the sorting date these 2 portfolios would have almost the same value. Past this date, the $1 invested in the low abnormal institutional ownership portfolio is always greater than the $1 invested in the high abnormal institutional ownership portfolio. Thus, these results indicate that financial institutions push prices away from fundamentals and then eventually they push them back towards fundamentals.

Consistent with the results found using abnormal ownership for all institutions, similar results are found using abnormal ownership for all 4 subgroups with the strongest results found for mutual funds. Figure 3.8 shows the how the value of $1 would change if it were invested in the low and high abnormal mutual fund ownership portfolio 37 months prior to formation. From this figure, we see a similar pattern as was found using abnormal institutional ownership.

3.2.3.4 Order Imbalance in Event Time

Next, I investigate whether the trades of financial institutions create large order imbalances between buys and sells. I define order imbalance as the net dollar change in ownership for each stock in the market. Dollar change in ownership is estimated using the average price prevailing over the reporting period. I calculate each stock's institutional order imbalance for all institutions and for banks, insurance companies, mutual funds, and other institutions. Then for the low and high abnormal institutional ownership portfolios I calculate the average order imbalance for the 12 quarters surrounding the formation date. The cumulative order imbalance for all institutions and for each of the 4 institution types is presented in Figures 3.9 and 3.10, respectively. From Figure 3.9, we can see that there is a large imbalance in institutional trades. Just prior to the allocation date, the cumulative average order imbalance reaches a level of almost -$300 million implying that in net the high portfolio has been bought more than the low portfolio. This result is confirmed when I disaggregate the order imbalance of the low and high portfolios and compare their order imbalances separately. From Figure 3.10, we can see that this large order imbalance is almost exclusively driven by mutual funds and other institutions and not by banks and insurance companies.

I investigate whether the pattern found using abnormal institutional ownership is also found using abnormal mutual fund ownership. However, I find a much different result. Whereas before, I was finding that the collective trades of mutual funds and other institutions drove the large change in abnormal institutional ownership, now I find that the large change in abnormal mutual fund ownership is almost exclusively driven by mutual funds. This result is shown in Figure 3.11. From this figure we can see the order imbalance created by banks, insurance companies, and other institutions is close to 0. However, there is an extremely large order imbalance created by mutual funds. The cumulative order imbalance reaches almost -$184 million at the allocation date, and in unreported results, I find that this is driven by mutual funds heavily buying securities in the high abnormal mutual fund ownership portfolio. Then following the allocation date, this order imbalance is reversed and I find that this is due to mutual funds selling the high portfolio and buying the low portfolio. This result suggests that the abnormal institutional ownership effect and the abnormal mutual fund ownership effect are separate phenomena.

3.2.3.5 Book-to-Market Ratio

So far, all of the results point towards financial institutions creating mispricing. To further investigate whether the results are due to mispricing, I investigate how the average book-to-market ratio of the high and low abnormal institutional ownership portfolio evolves over the 36 surrounding the allocation date. If prices are changing due to changes in fundamentals, then the book-to-market of the extreme portfolios should remain relatively constant. However, if institutions are driving prices away from fundamentals then for the high abnormal institutional portfolio we should see a large decline in the average book-to-market ratio prior to the allocation date and a large increase in the average book-to-market ratio following the allocation date. For the low abnormal institutional ownership portfolio, the opposite result should occur: There should be a large increase in the average book-to-market ratio prior to the allocation date and a large decline in the average book-to-market ratio following the allocation date. In Figure 3.12, I plot the average book-to-market ratio for the high and low abnormal institutional ownership portfolios. Consistent with the predictions for the high abnormal institutional portfolio, I find evidence that financial institutions are creating mispricing. Initially, 36 months before the allocation date the high and low abnormal institutional ownership portfolios have similar book-to-market ratios. However, this quickly changes as the book-to-market ratio of the high abnormal institutional ownership portfolio declines from an initial value of 0.73 to a value of 0.52. Then following formation, the book-to-market ratio of this portfolio more than doubles to a maximum value of 1.22, 32 months after formation. Thus there is substantial evidence that financial institutions push the price of the high abnormal institutional ownership portfolio away from fundamentals. For the low abnormal institutional ownership portfolio, there is much less evidence that the trades of financial institutions push prices away from fundamentals. Based on Figure 3.12, it looks like the book-to-market ratio of the low abnormal institutional ownership portfolio fluctuates without a clear upward or downward trend.

3.2.3.6 Average Portfolio Returns and Fama French (1993) Alphas

Next, I investigate how a strategy that purchased the low abnormal institutional ownership portfolio and sold the high abnormal institutional ownership portfolio would perform in the 1 year following the allocation date. After allocating each firm to an abnormal institutional ownership portfolio, following the methodology of Fama and French (2008), for each portfolio I calculate equally-weighted and value-weighted returns from July of year *t* until June of year *t+1*. Independent of the abnormal institutional ownership portfolio assignment, I also assign firms to 1 of 3 size portfolios using 30^{th} and 70^{th} percentile breakpoints. I calculate returns for the abnormal institutional ownership portfolios within each size group as well. Table 3.8 shows the average raw returns and the Fama and French (1993) alphas for each of the 10 abnormal institutional ownership portfolios and for size, abnormal institutional ownership portfolios. low abnormal institutional ownership firms have a much higher average raw return than high abnormal institutional ownership firms. The average equally-weighted raw return of the low portfolio is 2.80% while it is 0.05% for the high portfolio. Thus the low-high portfolio has a positive return close to 2.75%. This result is strongly related to firm size. For small firms the average low minus high equally-weighed return is 3.48%, for medium firms 1.70%, and for large firms 0.77%. This result is again consistent with financial institutions pushing prices away from fundamentals and is consistent with Amihud's suggestion that the returns to small firms are more sensitive to large trades. A similar result is found using value-weighted returns. However, the overall strategy produces a much lower return since more weight is given to large firms, i.e., firms that are less sensitive to institutional demand. Turning to the Fama and French (1993) alphas, I find that the return to the low minus high strategy is not materially affected after controlling for the 3 Fama and French factors. This suggests that these results are due to mispricing rather than risk.

I previously documented that institutional ownership was much lower in the early part of the sample and that institutional ownership increased from 1980 until 2010. Given this fact, one might wonder if the relation between abnormal institutional ownership and returns has strengthened over time. Table 3.9 shows the average raw returns and Fama and French alphas for the full sample, 1980-2011, as well as for the 1980s, 1990s, and 2000s. From 1980 until the end of 1989, the low minus high abnormal institutional ownership strategy earned an average raw return of 1.87% per month, then from 1990 until the end of 1999 this same strategy earned an average raw return of 3.55%, and finally from 2000 until the end of 2010 this strategy earned an average return of 2.89%. Thus, the relation has indeed strengthened over time, but it has weakened slightly since its high point in the 1990s. A similar result is found using value-weighted portfolios although the average returns are lower in magnitude. If we look at the Fama and French alphas, we can see a similar result of similar magnitude which suggests that this effect is likely due to mispricing.

3.2.3.7 Abnormal Institutional Ownership and Illiquidity

The prior results all seem to indicate that institutional demand pushes prices away from fundamentals. If this is indeed the case, then we would expect that illiquid firms would be more sensitive to institutional demand than liquid firms. For each firm I calculate the average1-month Amihud Illiquidity (ILIQ) measure using daily data. Independent of the abnormal institutional ownership portfolio allocation, I allocate firms to 1 of 3 illiquidity portfolios: low illiquidity, medium illiquidity, and high illiquidity using 30th and 70th percentile breakpoints. I then calculate portfolio returns for each of the 30 illiquidity, abnormal institutional ownership portfolios and report the results in Table 3.10.

Our suspicions are confirmed. The portfolio with high illiquidity has a much larger return compared to the low illiquidity portfolio. Using equally-weighted portfolios, the low illiquidity portfolio has an average raw return of 1.32% and an average Fama French alpha of 1.28% while the high illiquidity portfolio has an average raw return of 3.37% and an average Fama French alpha of 3.47%. Thus, institutional demand has a greater effect on illiquid securities than liquid securities.

3.2.3.8 Abnormal Ownership Strategy Returns by Institution Type

Previously, the Fama and MacBeth (1973) regression results indicated that there was a stronger effect created using abnormal institutional ownership and abnormal mutual fund ownership. In this section I investigate whether this result holds by repeating the prior portfolio analysis for portfolios constructed using abnormal bank, insurance, mutual fund, and other ownership. Each June, I sort stocks on abnormal bank, insurance, mutual fund, and other ownership and then calculate portfolio returns over the following 12 months. The average returns and Fama and French (1993) alphas from each of these strategies are reported in Table 3.11. The evidence indicates that the largest low-high portfolio return is earned using all financial institutions, but the strategy using abnormal mutual fund ownership earns an almost as large a return. For strategies formed using abnormal bank, insurance, mutual funds, and other ownership the average returns are, respectively, 1.39%, 0.96%, 2.40%, and 1.51%. Thus, the largest return is earned using abnormal mutual fund ownership and the smallest return is earned using insurance ownership. Fairly similar returns are found after controlling for the Fama and French (1993) factors. These results are consistent with the results found from the Fama-MacBeth regressions.

3.2.4 Abnormal Institutional Ownership and Other Institutional Demand Measures

The prior results showed that there is a negative relation between institutional demand and returns. The question remains, why do not I find the same result using other institutional demand measures. First, I investigate how institutional ownership and abnormal institutional ownership changes in event time for a strategy that trades on the change in institutional ownership. Previously, Nofsinger and Sias (1999) used to changes in institutional ownership to proxy for institutional ownership and found a positive relation between this variable and stock returns. Each June I allocate firms to 1 of 10 change in institutional ownership portfolios using NYSE breakpoints. Then, for each portfolio I calculate the cross-sectional mean institutional ownership for the 12 quarters surrounding the allocation date. The time series of mean abnormal institutional ownership for the high and low change in institutional ownership portfolios are plotted in Figure 3.13. For the high change in institutional ownership portfolio prior to the formation date, abnormal institutional ownership trends downward then there is a large increase in abnormal institutional ownership followed by a gradual decline in abnormal institutional ownership. I find a similar but opposite result for the low change in institutional ownership portfolio. Prior to the allocation date abnormal institutional ownership increases, then decreases sharply, and proceeds to increase slowly after the allocation date. Unlike when I formed portfolios using abnormal institutional ownership, here I find slower reversion in abnormal institutional ownership.

Next, I investigate how the average institutional ownership changes relative to the allocation date for the change in institutional ownership portfolios. The time series of mean institutional ownership for the high and low change in institutional ownership portfolios are plotted in Figure 3.14. For the high change in institutional ownership portfolio, there is a gradual increase in institutional ownership prior to the allocation date, then right before the allocation date there is a large positive jump in institutional ownership, followed by relatively little change in institutional ownership. Looking at the low change in institutional ownership portfolio's time series, there is also a gradual increase in institutional ownership, followed by a large negative jump in institutional ownership, and then a gradual increase in institutional ownership after the allocation date. These results seem to indicate that the reason that there is not a reversal found for portfolios formed on the change in institutional ownership is that these stocks do not experience as large a change in abnormal and raw institutional ownership as the stocks contained in the extreme abnormal institutional ownership portfolios.

Perhaps the most commonly used measure of institutional demand is the Lakonishok et al. (1992) herding measure. Each June, I allocate securities to 1 of 10 mutual fund herding portfolios: 5 buy herding portfolios and 5 sell herding portfolios. I then calculate how abnormal institutional ownership changes around the 12 quarters surrounding the allocation date for the strongest buy and sell herd portfolios. Figures 3.15 and 3.16 plot the time series of abnormal institutional ownership and institutional ownership for the strongest buy and sell herd portfolios. Looking at Figure 3.15, we can see that for the sell herd, initially there is a gradual increase in abnormal institutional ownership, followed by a fairly large decline in abnormal institutional ownership at the allocation quarter, and then a somewhat gradual increase in abnormal ownership in the following 12 quarters. For the strongest buy herd portfolio there is a gradual decline in abnormal institutional ownership, followed by an increase, and then a gradual decline. Compared to strategies sorted directly on abnormal institutional ownership, for the mutual fund herding strategy, the quarter-to-quarter change in abnormal institutional ownership is much more gradual.

In Figure 3.16 we can see that for the buy herd portfolio, institutional ownership is fairly flat prior to the allocation quarter and then increases and continues on a gradual upward trend following the allocation quarter. For the sell herd portfolio there is an increase in institutional ownership from 0.45 to 0.50 prior to the allocation quarter, then a decline in ownership between quarters -2 and +1, and then a gradual increase over the following 11 quarters. Thus, it appears that this measure does not capture the same level of price pressure that is found using abnormal institutional ownership.

Another proxy for institutional demand used in the literature is the Dasgupta et al. (2011) persistence measure. Each June I form 5 persistence portfolios, 1 portfolio for each of the values of persistence (persistence only takes the integer values of -3, -2, 0, 2, 3). I then calculate the cross-sectional average institutional ownership and abnormal institutional ownership. Figure 3.17 plots the average abnormal institutional ownership for the low and high persistence portfolios. From this figure, we can see that after the large change in abnormal institutional ownership prior to the allocation date, there is a gradual reversion in abnormal institutional ownership afterwards. Whereas the extreme abnormal institutional ownership portfolios had a swift reversion in abnormal institutional ownership, the extreme persistence portfolios have a much slower reversion in abnormal institutional ownership.

The time series of mean institutional ownership for the low and high persistence portfolios is plotted in Figure 3.18. For both extreme persistence portfolios there is only a small change in institutional ownership prior to the allocation date, then there is a large change in ownership around the allocation date, and then a gradual upward trend following the allocation date. This suggests that perhaps the reason that Dasgupta et al. (2011) find continuation in the short term is that there is a continuation in institutional ownership in the short term for securities in these 2 portfolios.

3.3 Conclusion

After controlling for trends in institutional ownership I find strong evidence that financial institutions push prices away from fundamentals. First, when abnormal institutional ownership is extremely high or low, I find that it quickly reverts towards 0. In conjunction with this finding, I also find that there is a reversal in returns and institutional trades. A strategy that purchases low institutional ownership securities and sells high institutional ownership securities has large negative returns prior to formation and positive returns in the year following formation. Theoretically, we would expect that institutional demand would have the largest effect on small firms and illiquid firms. This is exactly what I find. Within small firms, the low minus high abnormal institutional ownership strategy has an average raw return of 3.48% while within large firms, this same strategy averages 0.77%. Similarly, within highly illiquid securities this strategy earns an average return of 3.37%, but within low illiquid securities this strategy only earns an average return of 1.32%. These large returns remain even after controlling for the Fama and French (1993) factors which suggests that these results are due to mispricing rather than risk. Based on all of these results it seems that policies that increase liquidity would mitigate potential mispricing created by large institutional trades.

Table 3.1

Correlation between abnormal institutional ownership and other institutional ownership variables. This table shows the correlations between abnormal institutional ownership and other institutional ownership variables. Abnormal institutional ownership is calculated by de-trending institutional ownership for each security using the Hodrick-Prescott (1997) filter with λ equal to 1600. Change in abnormal institutional ownership is the quarterly change in abnormal institutional ownership. Change in institutional ownership is the quarterly change in institutional ownership. Institutional ownership is the fraction of shares outstanding that are held by financial institutions. Persistence is the Dasgupta et al. (2011) institutional persistence measure which counts the number of consecutive quarters over the prior 3 quarters that financial institutions have bought or sold a security. Nagel (2005) residual institutional ownership is as defined in Nagel (2005). Nagel calculates residual institutional ownership as the residual from the regression of logit institutional ownership on log firm size and squared log firm size. Mutual fund herding is the Lakonishok et al. (1992) herding measure as used in Wermers (1999). Mutual fund herding is defined as the buy herding measure if the stock is bought in net or as the sell herding measure if the stock is sold in net. Residual institutional ownership is the residual from the regression of institutional ownership on a constant and a time trend term. Change in residual institutional ownership is the 1 quarter change in residual institutional ownership. All variables are standardized by their cross-sectional mean and standard deviation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(1) Abnormal institutional ownership	1								
(2) Change in abnormal institutional ownership	0.52	1							
(3) Change in institutional ownership	0.50	0.98	1						
(4) Change in residual institutional ownership	0.51	0.99	0.99	1					
(5) Institutional ownership	0.35	0.18	0.18	0.17	1				
(6) Mutual fund herding	-0.08	0.00	0.00	0.00	-0.16	1			
(7) Nagel (2005) residual institutional ownership	0.33	0.18	0.18	0.18	0.59	-0.10	1		
(8) Persistence	0.28	0.28	0.31	0.30	0.07	0.03	0.08	1	
(9) Residual institutional ownership	0.82	0.39	0.37	0.37	0.42	-0.10	0.37	0.21	1

Table 3.2

Correlations between abnormal ownership variables. This table presents the correlations between 5 abnormal ownership measures: Abnormal institutional ownership, bank ownership, insurance ownership, mutual fund ownership, and other ownership. I classify the ownership of each institution in Thomson Reuters as a bank, insurance company, or nonbank and noninsurance company following the methodology of Lewellen (2011). I then calculate other ownership as the total nonbank and noninsurance institutional ownership minus mutual fund ownership. Mutual fund ownership is calculated from the Thomson Reuters mutual fund holdings database. I then calculate abnormal ownership for each institution subgroup using the Hodrick and Prescott (1997) filter with λ equal to 1600.

	(1)	(2)	(3)	(4)	(5)
(1) Abnormal institutional ownership	1				
(2) Abnormal bank ownership	0.43	1			
(3) Abnormal insurance ownership	0.33	0.06	1		
(4) Abnormal mutual fund ownership	0.49	0.13	0.12	1	
(5) Abnormal other ownership	0.73	0.07	0.03	0.01	1

Table 3.3

Fama-MacBeth regressions of annual stock returns on abnormal institutional ownership and other institutional ownership variables. The table reports Fama-MacBeth (1973) coefficient estimates from predictive regressions of annual returns on lagged abnormal institutional ownership and other institutional ownership variables. Returns are the annual return from July of year *t* until June of year *t+1*. Abnormal institutional ownership is calculated by detrending institutional ownership for each security using the Hodrick-Prescott (1997) filter with λ equal to 1600. Change in abnormal institutional ownership is the quarterly change in abnormal institutional ownership. Change in institutional ownership is the quarterly change in institutional ownership. Institutional ownership is the fraction of shares outstanding that are held by financial institutions. Persistence is the Dasgupta et al. (2011) institutional persistence measure which counts the number of consecutive quarters over the prior 3 quarters that financial institutions have bought or sold a security. Residual institutional is as defined in Nagel (2005). Nagel calculates residual institutional ownership as the residual from the regression of logit institutional ownership on log firm size and squared log firm size. Mutual fund herding is the Lakonishok et al. (1992) herding measure calculated using mutual fund data. All variables are standardized by their cross-sectional mean and standard deviation. I exclude financials (SIC codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with price less than $5 or greater than $1,000. I only use common shares with share codes equal to 10 or 11. Reported *t*-statistics (in parentheses) are adjusted for autocorrelation using Newey-West (1987) standard errors.

Panel A. All firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.1440	0.1441	0.1441	0.1441	0.1439	0.1348	0.1382	0.1331	0.1440
	(4.47)	(4.49)	(4.49)	(4.49)	(4.46)	(4.98)	(4.47)	(4.90)	(4.46)
Abnormal institutional ownership	-0.0958	.	.	.	.	.	.	.	.
	(-6.03)	.	.	.	.	.	.	.	.
Change in abnormal institutional ownership	.	-0.0154	.	.	.	.	.	.	.
	.	(-8.05)	.	.	.	.	.	.	.
Change in institutional ownership	.	.	0.0017	.	.	.	.	.	.
	.	.	(0.63)	.	.	.	.	.	.
Change in residual trend ownership	.	.	.	-0.0052	.	.	.	.	.
	.	.	.	(-2.20)	.	.	.	.	.
Institutional ownership	.	.	.	.	0.0052	.	.	.	.
	.	.	.	.	(0.66)	.	.	.	.
Mutual fund herding	.	.	.	.	.	-0.0033	.	.	.
	.	.	.	.	.	(-0.90)	.	.	.
Nagel (2005) residual institutional ownership	.	.	.	.	.	.	0.0169	.	.
	.	.	.	.	.	.	(3.10)	.	.
Persistence	.	.	.	.	.	.	.	-0.0028	.
	.	.	.	.	.	.	.	(-0.53)	.
Residual institutional ownership	.	.	.	.	.	.	.	.	-0.0897
	.	.	.	.	.	.	.	.	(-7.23)
Average adjusted r-squared	0.0308	0.0010	0.0004	0.0005	0.0051	0.0014	0.0044	0.0022	0.0264

Table 3.3 continued

Panel B. Small firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.1441	0.1538	0.1546	0.1543	0.1607	0.1428	0.1444	0.1430	0.1399
	(3.99)	(4.26)	(4.27)	(4.26)	(4.49)	(4.15)	(4.18)	(4.66)	(3.89)
Abnormal institutional ownership	-0.1511	.	.	.	.	.	.	.	.
	(-4.97)	.	.	.	.	.	.	.	.
Change in abnormal institutional ownership	.	-0.0260	.	.	.	.	.	.	.
	.	(-7.78)	.	.	.	.	.	.	.
Change in institutional ownership	.	.	0.0043	.	.	.	.	.	.
	.	.	(1.08)	.	.	.	.	.	.
Change in residual trend ownership	.	.	.	-0.0092	.	.	.	.	.
	.	.	.	(-3.08)	.	.	.	.	.
Institutional ownership	.	.	.	.	0.0150	.	.	.	.
	.	.	.	.	(1.53)	.	.	.	.
Mutual fund herding	.	.	.	.	.	-0.0064	.	.	.
	.	.	.	.	.	(-1.26)	.	.	.
Nagel (2005) residual institutional ownership	.	.	.	.	.	.	0.0270	.	.
	.	.	.	.	.	.	(3.94)	.	.
Persistence	.	.	.	.	.	.	.	0.0008	.
	.	.	.	.	.	.	.	(0.15)	.
Residual institutional ownership	.	.	.	.	.	.	.	.	-0.1428
	.	.	.	.	.	.	.	.	(-5.76)
Average adjusted r-squared	0.0468	0.0015	0.0003	0.0005	0.0048	-0.0024	0.0063	0.0013	0.0423

Panel C. Medium firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.1417	0.1373	0.1366	0.1369	0.1325	0.1387	0.1350	0.1248	0.1430
	(4.78)	(4.57)	(4.57)	(4.58)	(4.35)	(4.23)	(4.48)	(4.86)	(4.81)
Abnormal institutional ownership	-0.0783	.	.	.	.	.	.	.	.
	(-5.41)	.	.	.	.	.	.	.	.
Change in abnormal institutional ownership	.	-0.0058	.	.	.	.	.	.	.
	.	(-1.81)	.	.	.	.	.	.	.
Change in institutional ownership	.	.	0.0078	.	.	.	.	.	.
	.	.	(2.08)	.	.	.	.	.	.
Change in residual trend ownership	.	.	.	0.0028	.	.	.	.	.
	.	.	.	(0.79)	.	.	.	.	.
Institutional ownership	.	.	.	.	0.0167	.	.	.	.
	.	.	.	.	(2.30)	.	.	.	.
Mutual fund herding	.	.	.	.	.	-0.0041	.	.	.
	.	.	.	.	.	(-0.93)	.	.	.
Nagel (2005) residual institutional ownership	.	.	.	.	.	.	0.0145	.	.
	.	.	.	.	.	.	(2.15)	.	.
Persistence	.	.	.	.	.	.	.	-0.0010	.
	.	.	.	.	.	.	.	(-0.15)	.
Residual institutional ownership	.	.	.	.	.	.	.	.	-0.0696
	.	.	.	.	.	.	.	.	(-6.47)
Average adjusted r-squared	0.0316	0.0014	0.0020	0.0016	0.0064	0.0018	0.0047	0.0041	0.0245

Table 3.3 continued

Panel D. Large firms

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Constant	0.1413	0.1417	0.1417	0.1417	0.1343	0.1390	0.1394	0.1347	0.1418
	(5.05)	(5.14)	(5.13)	(5.13)	(5.02)	(4.97)	(4.92)	(4.86)	(5.09)
Abnormal institutional ownership	-0.0264	.	.	.	.	.	.	.	.
	(-2.61)	.	.	.	.	.	.	.	.
Change in abnormal institutional ownership	.	-0.0006	.	.	.	.	.	.	.
	.	(-0.15)	.	.	.	.	.	.	.
Change in institutional ownership	.	.	0.0026	.	.	.	.	.	.
	.	.	(0.53)	.	.	.	.	.	.
Change in residual trend ownership	.	.	.	0.0027	.	.	.	.	.
	.	.	.	(0.55)	.	.	.	.	.
Institutional ownership	.	.	.	.	0.0053	.	.	.	.
	.	.	.	.	(1.03)	.	.	.	.
Mutual fund herding	.	.	.	.	.	-0.0020	.	.	.
	.	.	.	.	.	(-0.28)	.	.	.
Nagel (2005) residual institutional ownership	.	.	.	.	.	.	0.0065	.	.
	.	.	.	.	.	.	(0.87)	.	.
Persistence	.	.	.	.	.	.	.	-0.0038	.
	.	.	.	.	.	.	.	(-0.72)	.
Residual institutional ownership	.	.	.	.	.	.	.	.	-0.0078
	.	.	.	.	.	.	.	.	(-1.16)
Average adjusted r-squared	0.0100	0.0025	0.0021	0.0029	0.0037	0.0029	0.0032	0.0053	0.0039

Table 3.4

Correlations between abnormal institutional ownership and other variables. This table presents correlations between abnormal institutional ownership and other variables. Abnormal institutional ownership is calculated by de-trending institutional ownership for each security using the Hodrick-Prescott (1997) filter with λ equal to 1600. Change in abnormal institutional ownership is the quarterly change in abnormal institutional ownership. Following Sloan (1996), I define accruals as: Accruals = (ΔCA – ΔCash) - (ΔCL – ΔSTD –ΔTP) – Dep, where ΔCA is the change in current assets, ΔCash is the change in cash and equivalents, ΔCL is the change in current liabilities, ΔSTD is the change in debt included in current liabilities, ΔTP is the change in income taxes payable, and Dep is the depreciation and amortization expense. Asset growth is defined as the year over year change in total assets divided by lagged total assets. This definition of asset growth was used in Cooper et al. (2008). Book-to-market ratio is calculated as book value of equity divided by market value of equity and is constructed following the methodology used in Fama and French (2008). Following Daniel and Titman (2006), I define composite share issuances as

$$\iota(t-5,t) = \log\left(\frac{ME_t}{ME_{t-5}}\right) - r(t-5,t)\ , \tag{17}$$

where ME_t is the firm's market equity today, ME_{t-5} is the firm's market equity 5 years ago, and r(t-5,t) is this firm's 5-year log return. Firm size is defined as share price multiplied by common shares outstanding. Gross profitability is defined as total revenue less cost of goods sold divided by total assets. This definition was used in Novy-Marx (2012). I follow the methodology of Ang, Hodrick, Xing, and Zhang (2009) and calculate idiosyncratic risk as the standard deviation of the residuals from a monthly regression of daily excess returns on the Fama and French (1993) 3-factor model. Excess returns are calculated as the difference between firm returns and the risk-free rate, the 1-month Treasury bill rate. I use the definition of investments-to-assets given in Stambaugh et al. (2012). They define investments to assets as the annual change in gross property, plant and equipment plus the annual change in inventories scaled by the lagged book value of assets. I define momentum as the compound return between month's *t*-12 and *t*-2. A similar definition was used in Fama and French (2008). Net stock issuances is defined as the log ratio of split adjusted shares to lagged split adjusted shares following Fama and French (2008). I use the definition of Ohlson's (1980) O-score that was used in Chen, Novy-Marx, and Zhang (2011). Ohlson's O-score measures the probability of bankruptcy and is calculated using a variety of accounting measures including: total assets, book value of debt, working capital, net income, etc. Persistence is the Dasgupta et al. (2011) institutional persistence measure which counts the number of consecutive quarters over the prior 3 quarters that financial institutions have bought or sold a security. Residual institutional is as defined in Nagel (2005). Nagel calculates residual institutional ownership as the residual from the regression of logit institutional ownership on log firm size and squared log firm size. Mutual fund herding is the Lakonishok et al. (1992) herding measure as in Wermers (1999). Mutual fund herding is defined as the buy herding measure if the stock was bought in net or the sell herding measure if the stock was sold in net. All variables are standardized by their cross-sectional mean and standard deviation.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
(1) Abnormal institutional ownership	1																	
(2) Accruals	0.04	1																
(3) Asset growth	0.02	0.19	1															
(4) Book-to-market ratio	-0.05	-0.14	-0.08	1														
(5) Daniel Titman (2006) composite	0.03	0.11	0.17	-0.13	1													
(6) Firm size	-0.01	-0.02	-0.01	-0.07	-0.06	1												
(7) Gross profitability	0.00	0.04	-0.06	-0.12	-0.15	0.01	1											
(8) Idiosyncratic risk	-0.01	0.06	0.05	-0.03	0.19	-0.15	-0.04	1										
(9) Investments to assets	0.01	-0.05	0.36	-0.03	0.09	0.00	-0.06	0.02	1									
(10) Momentum	0.08	0.00	0.00	-0.10	0.04	0.00	0.04	0.05	-0.01	1								
(11) Mutual fund herding	-0.08	0.01	0.02	0.00	0.05	-0.01	-0.02	0.12	0.01	0.10	1							
(12) Nagel residual institutional ownership	0.33	-0.03	-0.05	0.15	-0.05	0.00	0.07	-0.09	-0.04	-0.09	-0.10	1						
(13) Net stock issuances	0.02	0.09	0.20	-0.07	0.39	-0.03	-0.09	0.10	0.09	0.01	0.04	-0.05	1					
(14) O-score	-0.01	-0.06	0.02	0.07	0.17	-0.15	-0.35	0.20	0.04	0.04	0.05	-0.06	0.08	1				
(15) Persistence	0.28	0.02	0.02	-0.06	0.10	-0.05	-0.01	0.01	0.01	0.19	0.03	0.08	0.05	0.03	1			
(16) Return on assets	0.01	0.06	-0.25	-0.03	-0.14	0.03	0.21	-0.09	-0.17	-0.01	-0.03	0.06	-0.09	-0.34	-0.02	1		
(17) Return on equity	0.00	0.03	0.01	-0.02	-0.03	0.01	0.07	-0.03	-0.01	0.00	-0.01	0.01	0.01	-0.10	0.00	0.14	1	
(18) Share turnover	0.10	0.10	0.04	-0.21	0.22	0.00	0.00	0.26	0.02	0.17	0.05	0.13	0.07	-0.02	0.07	-0.02	0.00	1

Table 3.5

Fama-MacBeth regressions of annual stock returns on abnormal institutional ownership and other variables. The table reports Fama-MacBeth (1973) coefficient estimates from predictive regressions of annual returns on lagged abnormal institutional ownership and other financial variables. Returns are the annual return from July of year *t* until June of year *t+1*. Abnormal institutional ownership is the residual institutional ownership remaining after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Persistence is the Dasgupta et al. (2011) institutional trade persistence measure and residual institutional ownership is the Nagel (2005) residual institutional ownership measure. All independent variables are standardized each quarter using their cross-sectional mean and standard deviation. I exclude financials (SIC codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with price less than $5 or greater than $1,000. I only use common shares with share codes equal to 10 or 11. Reported *t*-statistics (in parentheses) are adjusted for autocorrelation using Newey-West (1987) standard errors. There are 3 different controls groups. Control group 1 is Daniel and Titman (2006) composite issuances and return on assets, control group 2 is all of the variables in control group 1 plus gross profitability and share turnover, control group 3 is all of the variables in control group 2 plus accruals, asset growth, book-to-market ratio, firm size, idiosyncratic risk, investments to assets, momentum, net issuances, O-score, and return on equity.

Panel A. All firms

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1440	0.1348	0.1306	0.1322	0.1041
	(4.47)	(5.42)	(4.99)	(4.93)	(3.13)
Abnormal institutional ownership	-0.0958	-0.1140	-0.1000	-0.0975	-0.1020
	(-6.03)	(-5.82)	(-5.61)	(-5.60)	(-4.86)
Mutual fund herding	.	-0.0043	-0.0059	-0.0057	-0.0076
	.	(-0.96)	(-1.37)	(-1.35)	(-2.06)
Nagel (2005) residual institutional ownership	.	0.0622	0.0545	0.0502	0.0568
	.	(4.60)	(3.87)	(4.25)	(4.05)
Persistence	.	0.0286	0.0225	0.0216	0.0172
	.	(4.86)	(5.22)	(4.82)	(4.14)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0308	0.0510	0.0622	0.0754	0.1014

Panel B. Small firms

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1441	0.0983	0.0839	0.0836	0.4848
	(3.99)	(4.12)	(3.03)	(2.72)	(1.99)
Abnormal institutional ownership	-0.1511	-0.2034	-0.1965	-0.2029	-0.1737
	(-4.97)	(-4.83)	(-4.75)	(-5.09)	(-2.91)
Mutual fund herding	.	-0.0037	0.0013	0.0013	-0.0004
	.	(-0.63)	(0.28)	(0.35)	(-0.10)
Nagel (2005) residual institutional ownership	.	0.1357	0.1417	0.1274	0.1880
	.	(6.50)	(4.61)	(5.39)	(3.08)
Persistence	.	0.0632	0.0470	0.0506	0.0183
	.	(6.10)	(5.80)	(5.54)	(0.73)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0468	0.0882	0.0835	0.0557	0.1244

Table 3.5 continued

Panel C. Medium firms

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1417	0.1371	0.1323	0.1318	0.1051
	(4.78)	(4.94)	(4.61)	(4.50)	(1.70)
Abnormal institutional ownership	-0.0783	-0.1127	-0.0996	-0.0969	-0.0965
	(-5.41)	(-5.15)	(-4.67)	(-4.82)	(-4.18)
Mutual fund herding	.	-0.0072	-0.0108	-0.0097	-0.0093
	.	(-1.33)	(-1.98)	(-1.80)	(-1.48)
Nagel (2005) residual institutional ownership	.	0.0676	0.0563	0.0555	0.0568
	.	(4.13)	(3.37)	(3.50)	(3.72)
Persistence	.	0.0329	0.0273	0.0261	0.0206
	.	(4.63)	(4.81)	(4.41)	(3.53)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0316	0.0576	0.0680	0.0832	0.1156

Panel D. Large firms

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1413	0.1379	0.1341	0.1326	0.1213
	(5.05)	(4.84)	(5.19)	(4.54)	(2.37)
Abnormal institutional ownership	-0.0264	-0.0339	-0.0282	-0.0248	-0.0283
	(-2.61)	(-2.80)	(-2.46)	(-2.15)	(-2.03)
Mutual fund herding	.	-0.0030	-0.0070	-0.0080	-0.0037
	.	(-0.51)	(-1.43)	(-1.97)	(-1.09)
Nagel (2005) residual institutional ownership	.	0.0157	0.0172	0.0090	0.0187
	.	(1.81)	(1.88)	(1.09)	(1.78)
Persistence	.	0.0033	0.0035	0.0033	-0.0004
	.	(0.54)	(0.70)	(0.64)	(-0.09)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0100	0.0212	0.0470	0.0800	0.1328

Table 3.6

Fama-MacBeth regressions of annual stock returns on abnormal ownership and other variables by ownership subgroup. The table reports Fama-MacBeth (1973) coefficient estimates from predictive regressions of annual returns on lagged abnormal ownership and other financial variables. Each model is estimated using abnormal bank ownership, insurance, mutual fund, and other financial institutions ownership. Returns are the annual return from July of year *t* until June of year *t+1*. Abnormal ownership is the residual ownership remaining after removing the trend from ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Persistence is the Dasgupta et al. (2011) institutional trade persistence measure and residual institutional ownership is the Nagel (2005) residual institutional ownership measure. All independent variables are standardized each quarter using their cross-sectional mean and standard deviation. I exclude financials (SIC codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with price less than \$5 or greater than \$1,000. I only use common shares with share codes equal to 10 or 11. Reported *t*-statistics (in parentheses) are adjusted for autocorrelation using Newey-West (1987) standard errors. There are 3 different controls groups. Control group 1 is Daniel and Titman (2006) composite issuances and return on assets, control group 2 is all of the variables in control group 1 plus gross profitability and share turnover, control group 3 is all of the variables in control group 2 plus accruals, asset growth, book-to-market ratio, firm size, idiosyncratic risk, investments to assets, momentum, net issuances, O-score, and return on equity.

Panel A. Banks

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1452	0.1309	0.1309	0.1329	0.1020
	(4.48)	(5.37)	(5.04)	(4.98)	(3.05)
Abnormal bank ownership	-0.0428	-0.0419	-0.0336	-0.0317	-0.0304
	(-5.54)	(-5.46)	(-5.69)	(-5.65)	(-5.76)
Mutual fund herding	.	-0.0049	-0.0058	-0.0056	-0.0073
	.	(-1.29)	(-1.60)	(-1.57)	(-2.26)
Nagel residual institutional ownership	.	0.0158	0.0157	0.0121	0.0135
	.	(2.48)	(1.98)	(2.23)	(2.05)
Persistence	.	0.0022	0.0022	0.0017	-0.0003
	.	(0.44)	(0.75)	(0.61)	(-0.15)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0064	0.0145	0.0334	0.0475	0.0722

Table 3.6 continued

Panel B. Insurance

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1514	0.1314	0.1316	0.1336	0.1010
	(4.46)	(5.35)	(5.04)	(5.01)	(2.98)
Abnormal insurance ownership	-0.0298	-0.0323	-0.0256	-0.0248	-0.0238
	(-4.64)	(-5.13)	(-5.32)	(-5.17)	(-4.90)
Mutual fund herding	.	-0.0038	-0.0053	-0.0049	-0.0067
	.	(-1.04)	(-1.47)	(-1.37)	(-2.08)
Nagel (2005) residual institutional ownership	.	0.0101	0.0100	0.0071	0.0083
	.	(1.85)	(1.49)	(1.54)	(1.51)
Persistence	.	-0.0006	-0.0001	-0.0002	-0.0020
	.	(-0.11)	(-0.02)	(-0.05)	(-0.89)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0034	0.0112	0.0311	0.0457	0.0711

Panel C. Mutual funds

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1472	0.1346	0.1320	0.1337	0.1058
	(4.45)	(5.45)	(5.03)	(4.96)	(3.15)
Abnormal insurance ownership	-0.0835	-0.0728	-0.0574	-0.0563	-0.0548
	(-5.20)	(-4.36)	(-4.01)	(-4.16)	(-4.04)
Mutual fund herding	.	-0.0068	-0.0078	-0.0076	-0.0094
	.	(-1.94)	(-2.33)	(-2.25)	(-3.16)
Nagel (2005) residual institutional ownership	.	0.0233	0.0197	0.0166	0.0201
	.	(3.37)	(2.56)	(2.95)	(2.99)
Persistence	.	0.0074	0.0047	0.0044	0.0005
	.	(1.54)	(1.47)	(1.32)	(0.24)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0243	0.0336	0.0452	0.0591	0.0835

Table 3.6 continued

Panel D. Other financial institutions

	(1)	(2)	(3)	(4)	(5)
Intercept	0.1494	0.1311	0.1321	0.1339	0.0999
	(4.45)	(5.33)	(5.12)	(5.05)	(3.04)
Abnormal other institutions ownership	-0.0560	-0.0511	-0.0427	-0.0422	-0.0429
	(-8.91)	(-7.32)	(-7.34)	(-7.21)	(-5.93)
Mutual fund herding	.	-0.0013	-0.0029	-0.0025	-0.0041
	.	(-0.30)	(-0.71)	(-0.59)	(-1.06)
Nagel (2005) residual institutional ownership	.	0.0241	0.0199	0.0178	0.0197
	.	(2.79)	(2.35)	(2.58)	(2.59)
Persistence	.	0.0079	0.0068	0.0066	0.0042
	.	(1.51)	(2.03)	(2.03)	(1.60)
Controls group 1	No	No	Yes	Yes	Yes
Controls group 2	No	No	No	Yes	Yes
Controls group 3	No	No	No	No	Yes
Average adjusted r-squared	0.0113	0.0192	0.0356	0.0506	0.0760

Table 3.7

Abnormal institutional ownership deciles: descriptive statistics. At the end of June of each year from 1980 to 2010 I allocate firms to 10 decile portfolios based on abnormal institutional ownership. Abnormal institutional ownership is calculated by de-trending institutional ownership using the Hodrick-Prescott filter with λ equal to 1600. The table reports the time series average of annual medians at the time of portfolio formation for 18 financial variables. Abnormal INST is defined as abnormal institutional ownership. INST is institutional ownership defined as the fraction of shares outstanding held by financial institutions. Mutual fund herding is the Lakonishok et al. (1992) herding measure calculated as in Wermers (1999). NAGEL INST is residual institutional ownership after controlling for firm size as in Nagel (2005). Persistence is the institutional trade persistence measure from Dasgupta, Prat, and Verardo (2011). Accruals is defined as in Sloan (1996). Asset growth is the annual growth in assets as defined in Cooper et al. (2008), BM is the book-to-market ratio as defined in Fama and French (1993). DT Composite is the Daniel and Titman (2006) composite issuance measure. Firm size is market capitalization in millions of dollars. Gross Profit is the gross profits-to-assets measure from Novy-Marx (2012). Idiosyncratic risk is defined as in Ang, Hodrick, Xing, and Zhang (2009). Investments to asset is defined as in Stambaugh, Yu, and Yuan (2012) who define investments to assets as the annual change in gross property, plant and equipment plus the annual change in inventories scaled by the lagged book value of assets. Momentum is the lagged compound return from month's *t*-12 to *t*-2. NS is net stock issuances from Fama and French (2008). Net stock issuances is defined as the log ratio of split adjusted shares to lag split adjusted shares. O-Score is the Ohlson (1980) measure. ROA is return on assets defined as income before extraordinary items divided by lagged total assets. This definition of return on assets was used in Fama and French (2006). ROE is return on equity defined as in Chen, Novy-Marx, and Zhang (2011) who define Return on Equity as income before extraordinary items divided by book equity. Share turnover is the log of share traded divided by shares outstanding.

Decile	Abnormal INST	INST	Mutual fund herding	Nagel INST	Persistence	Accruals	Asset growth	BM	DT Composite	Firm Size
1(Low)	-0.0890	0.3472	0.0527	-0.1121	-0.0667	-0.0123	0.1103	0.6340	0.0653	269.2746
2	-0.0436	0.3907	0.0279	0.0590	-0.0667	-0.0100	0.1023	0.6040	0.0086	328.8708
3	-0.0246	0.3978	0.0253	0.0924	-0.0667	-0.0151	0.0916	0.5942	-0.0258	311.0929
4	-0.0126	0.3758	0.0261	0.0351	-0.0667	-0.0147	0.0925	0.5746	-0.0468	348.4911
5	-0.0029	0.3443	0.0202	0.0011	0.0000	-0.0171	0.0897	0.5655	-0.0469	323.5517
6	0.0064	0.3823	0.0239	0.1123	0.0000	-0.0165	0.0919	0.5819	-0.0473	322.9651
7	0.0169	0.4295	0.0264	0.2778	0.0667	-0.0127	0.0967	0.5606	-0.0392	335.8681
8	0.0309	0.4722	0.0228	0.4532	0.2000	-0.0114	0.1024	0.5596	-0.0189	338.3390
9	0.0534	0.5210	0.0278	0.6064	0.9000	-0.0065	0.1221	0.5173	0.0136	332.1178
10 (High)	0.1064	0.6265	0.0363	1.1883	1.8833	0.0060	0.1685	0.4728	0.1067	340.0640
Spread (1-10)	-0.1953	-0.2793	0.0164	-1.3004	-1.9500	-0.0183	-0.0582	0.1612	-0.0414	-70.7893
t(spread)	-32.97	-19.69	4.62	-6.17	-13.49	-7.25	-7.25	6.30	-3.51	-3.01

Table 3.7 continued

Decile	Gross Profit	Idiosyncratic risk	Investments to assets	Momentum	NS	O-Score	ROA	ROE	Share turnover
1(Low)	0.3503	2.2789	0.0393	0.0696	0.0114	-1.0382	0.0468	0.0975	-6.9608
2	0.3652	2.0658	0.0369	0.0804	0.0076	-1.2187	0.0536	0.1084	-7.1736
3	0.3696	1.9627	0.0363	0.0888	0.0050	-1.3814	0.0579	0.1128	-7.3319
4	0.3659	1.9192	0.0352	0.0981	0.0043	-1.3478	0.0596	0.1194	-7.4387
5	0.3635	1.9399	0.0366	0.1085	0.0041	-1.3151	0.0585	0.1174	-7.5333
6	0.3646	1.9041	0.0365	0.1116	0.0041	-1.4226	0.0601	0.1184	-7.4829
7	0.3722	1.8896	0.0360	0.1197	0.0056	-1.4564	0.0601	0.1194	-7.3821
8	0.3637	1.9532	0.0356	0.1358	0.0078	-1.3775	0.0594	0.1196	-7.2400
9	0.3676	2.0538	0.0360	0.1633	0.0111	-1.3768	0.0595	0.1209	-7.0468
10 (High)	0.3604	2.2058	0.0412	0.2331	0.0217	-1.2554	0.0596	0.1233	-6.6703
Spread (1-10)	-0.0100	0.0732	-0.0019	-0.1635	-0.0104	0.2172	-0.0128	-0.0258	-0.2905
t(spread)	-1.66	1.79	-1.30	-5.40	-5.52	3.05	-4.60	-5.74	-7.09

Table 3.8

Abnormal institutional ownership portfolio returns. At the end of June of year *t* stocks are allocated to 10 decile portfolios based on abnormal institutional ownership. Abnormal institutional ownership is the residual ownership remaining after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Each portfolio is held from July of year *t* until June of year *t+1*. Equally-weighted and value-weighted returns are calculated each month. At the time of formation, I exclude stocks with price less than \$5 or greater than \$1,000 and exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999). I only use common equity securities with share code equal to 10 or 11. I report average monthly returns for all firms and for 3 size-sorted groups. Small firms are defined as firms with market equity less than the 30^{th} percentile, medium firms are defined as firms with market equity greater than or equal to the 30^{th} percentile and less than or equal to the 70^{th} percentile, and large firms are defined as firms with market equity greater than the 70^{th} percentile. Decile breakpoints are based on common shares traded on the New York Stock Exchange (NYSE). Panel A.1 shows average raw returns for equally-weighted portfolios, Panel A.2 shows average raw returns for value-weighted portfolios, Panel B.1 shows Fama and French (1993) alphas for equally-weighted portfolios, and Panel B.2 shows Fama and French (1993) alphas for value-weighted portfolios. The *t*-statistics are adjusted for auto-correlation using Newey West (1987) standard errors.

Panel A. Raw return portfolios by size group

Panel A.1 Equally-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0280	0.0196	0.0150	0.0115	0.0094	0.0086	0.0072	0.0077	0.0052	0.0005	0.0275	13.22
Small firms	0.0327	0.0225	0.0162	0.0114	0.0085	0.0071	0.0052	0.0058	0.0026	-0.0021	0.0348	14.07
Medium firms	0.0210	0.0173	0.0148	0.0126	0.0123	0.0111	0.0104	0.0104	0.0090	0.0041	0.0170	7.71
Large firms	0.0158	0.0125	0.0120	0.0118	0.0117	0.0106	0.0102	0.0106	0.0087	0.0081	0.0077	3.19

Panel A.2 Value-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0164	0.0133	0.0110	0.0111	0.0111	0.0100	0.0094	0.0108	0.0074	0.0047	0.0117	6.16
Small firms	0.0289	0.0209	0.0154	0.0109	0.0092	0.0077	0.0062	0.0064	0.0025	-0.0022	0.0311	12.65
Medium firms	0.0187	0.0169	0.0141	0.0125	0.0127	0.0111	0.0104	0.0106	0.0086	0.0049	0.0138	6.89
Large firms	0.0130	0.0112	0.0103	0.0109	0.0111	0.0101	0.0097	0.0110	0.0077	0.0073	0.0057	2.36

Table 3.8 continued

Panel B. Raw return portfolios by size group

Panel B.1 Equally-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0156	0.0078	0.0033	0.0001	-0.0022	-0.0031	-0.0047	-0.0043	-0.0073	-0.0124	0.0279	13.66
Small firms	0.0203	0.0108	0.0044	-0.0004	-0.0033	-0.0045	-0.0070	-0.0064	-0.0100	-0.0153	0.0356	14.46
Medium firms	0.0084	0.0051	0.0029	0.0012	0.0003	-0.0012	-0.0015	-0.0017	-0.0034	-0.0087	0.0170	7.99
Large firms	0.0048	0.0019	0.0013	0.0012	0.0012	-0.0002	-0.0007	-0.0004	-0.0025	-0.0016	0.0063	2.59

Panel B.2 Value-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0055	0.0028	0.0014	0.0011	0.0018	-0.0002	-0.0002	0.0003	-0.0039	-0.0065	0.0121	6.60
Small firms	0.0168	0.0089	0.0034	-0.0013	-0.0029	-0.0044	-0.0062	-0.0060	-0.0101	-0.0152	0.0320	12.93
Medium firms	0.0068	0.0046	0.0024	0.0013	0.0007	-0.0010	-0.0014	-0.0011	-0.0037	-0.0073	0.0142	7.34
Large firms	0.0029	0.0012	0.0009	0.0011	0.0021	0.0003	0.0005	0.0011	-0.0030	-0.0019	0.0047	1.96

Table 3.9

Abnormal institutional ownership portfolio returns by subperiod. At the end of June of year *t* stocks are allocated to 10 decile portfolios based on abnormal institutional ownership. Abnormal institutional ownership is the residual ownership remaining after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Each portfolio is held from July of year *t* until June of year *t+1*. Equally-weighted and value-weighted returns are calculated each month. At the time of formation, I exclude stocks with price less than \$5 or greater than \$1,000 and exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999). I only use common equity securities with share code equal to 10 or 11. I report average monthly returns for all firms and for 3 size-sorted groups. Decile breakpoints are based on common shares traded on the New York Stock Exchange (NYSE). Panels A.1 and A.2 show average raw returns by sub period for equally-weighted and value-weighted portfolios, respectively. Panels B.1 and B.2 show Fama and French (1993) alphas by sub period for equally-weighted and value-weighted portfolios, respectively. The *t*-statistics are adjusted for auto-correlation using Newey West (1987) standard errors.

Panel A. Raw return portfolios by subperiod

Panel A.1 Equally-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
1980-2011	0.0280	0.0196	0.0150	0.0115	0.0094	0.0086	0.0072	0.0077	0.0052	0.0005	0.0275	13.22
1980-1989	0.0261	0.0205	0.0171	0.0160	0.0118	0.0120	0.0109	0.0107	0.0100	0.0075	0.0187	11.39
1990-1999	0.0339	0.0209	0.0145	0.0100	0.0071	0.0073	0.0059	0.0074	0.0052	-0.0016	0.0355	15.78
2000-2011	0.0250	0.0178	0.0140	0.0089	0.0093	0.0069	0.0047	0.0053	0.0008	-0.0038	0.0289	6.26

Panel A.2 Value-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
1980-2011	0.0164	0.0133	0.0110	0.0111	0.0111	0.0100	0.0094	0.0108	0.0074	0.0047	0.0117	6.16
1980-1989	0.0189	0.0162	0.0154	0.0142	0.0160	0.0153	0.0154	0.0138	0.0122	0.0100	0.0089	3.07
1990-1999	0.0234	0.0160	0.0147	0.0151	0.0155	0.0146	0.0146	0.0152	0.0121	0.0068	0.0167	5.20
2000-2011	0.0079	0.0085	0.0039	0.0049	0.0027	0.0013	-0.0010	0.0044	-0.0015	-0.0023	0.0102	2.83

Table 3.9 continued

Panel B. Fama-French monthly alphas by subperiod

Panel B.1 Equally-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
1980-2011	0.0156	0.0078	0.0033	0.0001	-0.0022	-0.0031	-0.0047	-0.0043	-0.0073	-0.0124	0.0279	13.66
1980-1989	0.0119	0.0059	0.0023	0.0015	-0.0027	-0.0024	-0.0025	-0.0032	-0.0041	-0.0063	0.0182	13.49
1990-1999	0.0185	0.0063	0.0009	-0.0025	-0.0055	-0.0052	-0.0074	-0.0063	-0.0088	-0.0165	0.0350	17.61
2000-2011	0.0175	0.0123	0.0082	0.0035	0.0034	0.0015	-0.0006	-0.0001	-0.0047	-0.0086	0.0262	7.71

Panel B.2 Value-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
1980-2011	0.0055	0.0028	0.0014	0.0011	0.0018	-0.0002	-0.0002	0.0003	-0.0039	-0.0065	0.0121	6.60
1980-1989	0.0047	0.0014	0.0012	-0.0009	0.0029	0.0016	0.0027	-0.0001	-0.0017	-0.0034	0.0081	2.99
1990-1999	0.0086	0.0017	0.0010	0.0012	0.0010	0.0015	-0.0004	0.0013	-0.0032	-0.0083	0.0169	5.22
2000-2011	0.0056	0.0070	0.0045	0.0044	0.0008	-0.0009	-0.0016	0.0027	-0.0036	-0.0038	0.0093	3.52

Table 3.10

Abnormal institutional ownership portfolio returns by Amihud illiquidity. At the end of June of year *t* stocks are allocated to 10 decile portfolios based on abnormal institutional ownership. Independent of the abnormal institutional ownership portfolio allocation, stocks are also allocated to 3 illiquidity portfolios. Illiquidity is defined as the 1-month Amihud (2002) illiquidity measure calculated for each firm. Stocks are assigned to the low illiquidity portfolio if they have illiquidity less than the 30th percentile, to the medium illiquidity portfolio if they have illiquidity between the 30th and 70th percentile, and to the high illiquidity portfolio if they have illiquidity greater than the 70th percentile. Illiquidity breakpoints are determined using all common shares traded on the NYSE that have a share price greater than \$5 and less than \$1,000 and that are not a financial or utility firm. Abnormal institutional ownership is the residual ownership remaining after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Each portfolio is held from July of year *t* until June of year *t+1*. Equally-weighted and value-weighted returns are calculated each month. At the time of formation, I exclude stocks with price less than \$5 or greater than \$1,000 and exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999). I only use common equity securities with share code equal to 10 or 11. I report average monthly returns for all firms and for 3 illiquidity-sorted groups. Panel A.1 shows average raw returns for equally-weighted portfolios, Panel A.2 shows average raw returns for value-weighted portfolios, Panel B.1 shows Fama and French (1993) alphas for equally-weighted portfolios, and Panel B.2 shows Fama and French (1993) alphas for value-weighted portfolios. The *t*-statistics are adjusted for auto-correlation using Newey West (1987) standard errors.

Panel A. Raw return portfolios by Amihud illiquidity group

Panel A.1 Equally-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0280	0.0196	0.0150	0.0115	0.0094	0.0086	0.0072	0.0077	0.0052	0.0005	0.0275	13.22
Low ILIQ	0.0203	0.0162	0.0146	0.0136	0.0116	0.0116	0.0100	0.0118	0.0079	0.0071	0.0132	6.13
Medium ILIQ	0.0228	0.0170	0.0145	0.0123	0.0108	0.0090	0.0099	0.0090	0.0071	0.0007	0.0221	9.79
High ILIQ	0.0326	0.0223	0.0157	0.0108	0.0083	0.0071	0.0046	0.0057	0.0034	-0.0012	0.0337	12.01

Panel A.2 Value-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0164	0.0133	0.0110	0.0111	0.0111	0.0100	0.0094	0.0108	0.0074	0.0047	0.0117	6.16
Low ILIQ	0.0135	0.0119	0.0104	0.0110	0.0114	0.0102	0.0098	0.0113	0.0076	0.0068	0.0066	2.83
Medium ILIQ	0.0192	0.0160	0.0142	0.0120	0.0108	0.0098	0.0102	0.0093	0.0079	0.0033	0.0159	7.42
High ILIQ	0.0258	0.0202	0.0146	0.0108	0.0098	0.0088	0.0054	0.0070	0.0037	0.0005	0.0253	8.74

Table 3.10 continued

Panel B. Fama-French monthly alphas by Amihud illiquidity group

Panel B.1 Equally-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0156	0.0078	0.0033	0.0001	-0.0022	-0.0031	-0.0047	-0.0043	-0.0073	-0.0124	0.0279	13.66
Low ILIQ	0.0093	0.0055	0.0038	0.0032	0.0014	0.0011	-0.0004	0.0012	-0.0031	-0.0035	0.0128	6.20
Medium ILIQ	0.0101	0.0047	0.0027	0.0007	-0.0012	-0.0032	-0.0020	-0.0034	-0.0057	-0.0123	0.0223	9.72
High ILIQ	0.0199	0.0104	0.0036	-0.0010	-0.0039	-0.0049	-0.0078	-0.0066	-0.0094	-0.0147	0.0347	12.59

Panel B.2 Value-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All firms	0.0055	0.0028	0.0014	0.0011	0.0018	-0.0002	-0.0002	0.0003	-0.0039	-0.0065	0.0121	6.60
Low ILIQ	0.0033	0.0018	0.0010	0.0012	0.0023	0.0005	0.0006	0.0014	-0.0031	-0.0028	0.0061	2.63
Medium ILIQ	0.0074	0.0038	0.0028	0.0006	-0.0010	-0.0022	-0.0017	-0.0027	-0.0044	-0.0090	0.0164	7.43
High ILIQ	0.0135	0.0083	0.0027	-0.0009	-0.0023	-0.0034	-0.0066	-0.0053	-0.0091	-0.0131	0.0265	9.35

Table 3.11

Abnormal ownership portfolio returns by institution subgroup. At the end of June of year *t* stocks are allocated to 10 decile portfolios based on abnormal ownership calculated using all institution ownership, bank ownership, insurance ownership, mutual fund ownership, or other ownership. Abnormal ownership breakpoints are determined using all common shares traded on the NYSE that have a share price greater than \$5 and less than \$1,000 and that are not a financial or utility firm. Abnormal ownership is the residual ownership remaining after removing the trend from ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Each portfolio is held from July of year *t* until June of year *t+1*. Equally-weighted and value-weighted returns are calculated each month. At the time of formation, I exclude stocks with price less than \$5 or greater than \$1,000 and exclude financial firms and utilities (SIC codes 6000-6999 and 4900-4999). I only use common equity securities with share code equal to 10 or 11. I report average monthly returns for portfolios formed using abnormal institution ownership for all institutions and for the 4 institution subgroups. Panel A.1 shows average raw returns for equally-weighted portfolios, Panel A.2 shows average raw returns for value-weighted portfolios, Panel B.1 shows Fama and French (1993) alphas for equally-weighted portfolios, and Panel B.2 shows Fama and French (1993) alphas for value-weighted portfolios. The *t*-statistics are adjusted for auto-correlation using Newey West (1987) standard errors.

Panel A. Raw return portfolios by abnormal ownership subgroup

Panel A.1 Equally-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles										
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All institutions	0.0280	0.0196	0.0150	0.0115	0.0094	0.0086	0.0072	0.0077	0.0052	0.0005	0.0275	13.22
Banks	0.0205	0.0185	0.0172	0.0137	0.0105	0.0081	0.0073	0.0073	0.0079	0.0066	0.0139	10.50
Insurance	0.0180	0.0185	0.0178	0.0145	0.0103	0.0084	0.0096	0.0087	0.0101	0.0084	0.0096	9.69
Mutual funds	0.0265	0.0181	0.0152	0.0127	0.0096	0.0084	0.0090	0.0078	0.0067	0.0025	0.0240	11.86
Other	0.0217	0.0162	0.0136	0.0120	0.0095	0.0096	0.0100	0.0092	0.0083	0.0066	0.0151	14.29

Panel A.2 Value-weighted portfolio average monthly raw returns

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All institutions	0.0164	0.0133	0.0110	0.0111	0.0111	0.0100	0.0094	0.0108	0.0074	0.0047	0.0117	6.16
Banks	0.0132	0.0141	0.0131	0.0115	0.0104	0.0099	0.0088	0.0075	0.0082	0.0071	0.0061	4.24
Insurance	0.0113	0.0140	0.0117	0.0113	0.0091	0.0107	0.0100	0.0081	0.0092	0.0083	0.0030	2.07
Mutual funds	0.0166	0.0129	0.0119	0.0100	0.0106	0.0093	0.0110	0.0101	0.0082	0.0057	0.0110	6.12
Other	0.0126	0.0117	0.0109	0.0110	0.0094	0.0097	0.0108	0.0119	0.0105	0.0073	0.0053	3.56

Table 3.11 continued

Panel B. Fama-French monthly alphas by abnormal ownership subgroup

Panel B.1 Equally-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All institutions	0.0156	0.0078	0.0033	0.0001	-0.0022	-0.0031	-0.0047	-0.0043	-0.0073	-0.0124	0.0279	13.66
Banks	0.0081	0.0061	0.0049	0.0015	-0.0012	-0.0034	-0.0043	-0.0043	-0.0043	-0.0063	0.0144	10.82
Insurance	0.0053	0.0063	0.0054	0.0025	-0.0015	-0.0032	-0.0023	-0.0032	-0.0021	-0.0045	0.0098	9.55
Mutual funds	0.0142	0.0058	0.0028	0.0010	-0.0019	-0.0031	-0.0026	-0.0045	-0.0056	-0.0105	0.0246	12.79
Other	0.0092	0.0043	0.0019	-0.0001	-0.0020	-0.0020	-0.0018	-0.0029	-0.0040	-0.0063	0.0155	14.45

Panel B.2 Value-weighted portfolio monthly Fama-French alphas

	Abnormal institutional ownership deciles											
	1(Low)	2	3	4	5	6	7	8	9	10 (High)	Spread (1-10)	t(spread)
All institutions	0.0055	0.0028	0.0014	0.0011	0.0018	-0.0002	-0.0002	0.0003	-0.0039	-0.0065	0.0121	6.60
Banks	0.0021	0.0034	0.0033	0.0023	0.0013	0.0002	-0.0009	-0.0019	-0.0027	-0.0044	0.0064	4.48
Insurance	-0.0001	0.0030	0.0014	0.0016	-0.0003	0.0011	0.0011	-0.0009	-0.0009	-0.0030	0.0029	1.88
Mutual funds	0.0060	0.0020	0.0012	0.0004	0.0016	0.0004	0.0014	-0.0004	-0.0026	-0.0055	0.0115	6.99
Other	0.0015	0.0014	0.0009	0.0009	0.0002	0.0004	0.0004	0.0015	-0.0002	-0.0042	0.0057	3.96

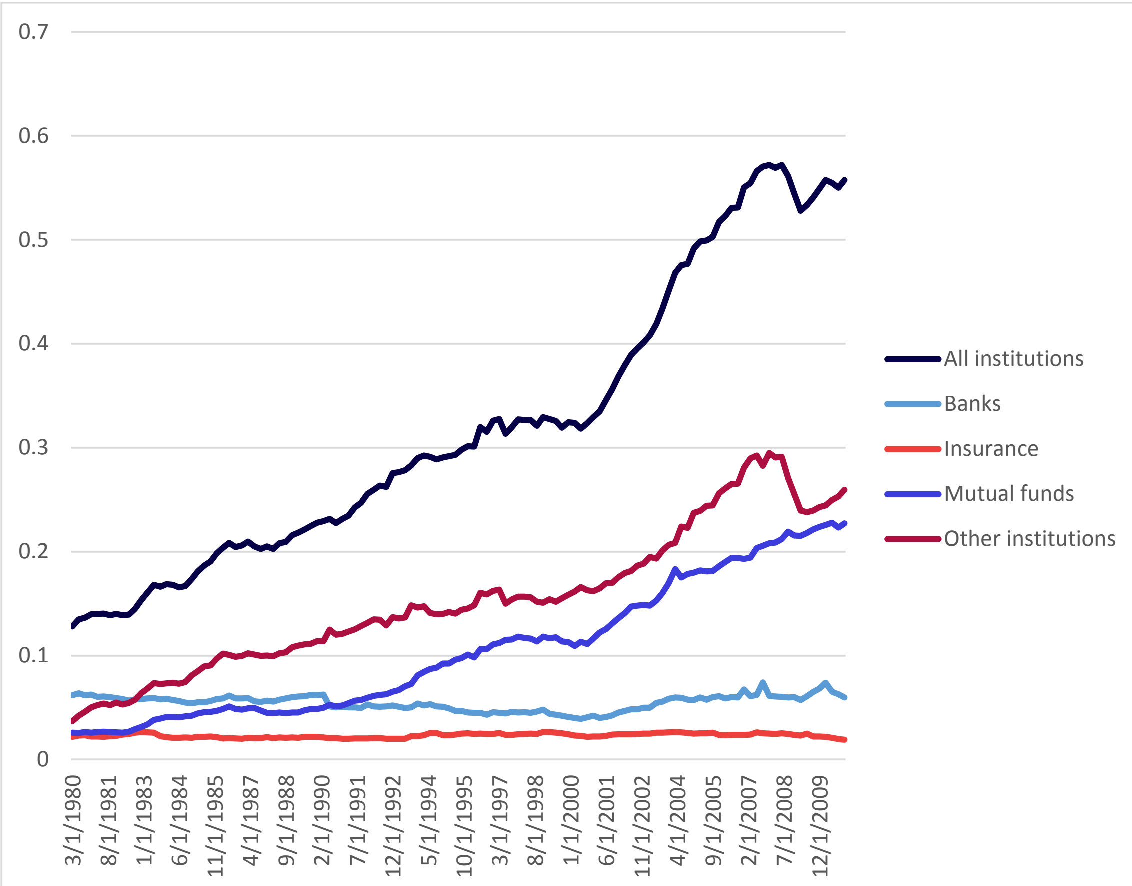

Figure 3.1 Times series of equally-weighted institutional ownership. The figure plots the time series of institutional ownership, bank ownership, insurance ownership, mutual fund ownership, and other institutions ownership for all common equity securities traded on the NYSE/NASDAQ/AMEX exchanges with share codes equal to 10 and 11. Institutional ownership is defined as the fraction of securities held by all financial institutions while bank, insurance, mutual fund, and other institutions ownership is the fraction of securities held by that type of institution. Institutions are classified using the methodology used in Lewellen (2011). Mutual fund ownership is from the Thomson Reuters mutual fund holdings database. All other ownership measures are calculated using data from the Thomson Reuters institutional holdings database. Ownership variables are calculated for the whole market by equally-weighting all securities.

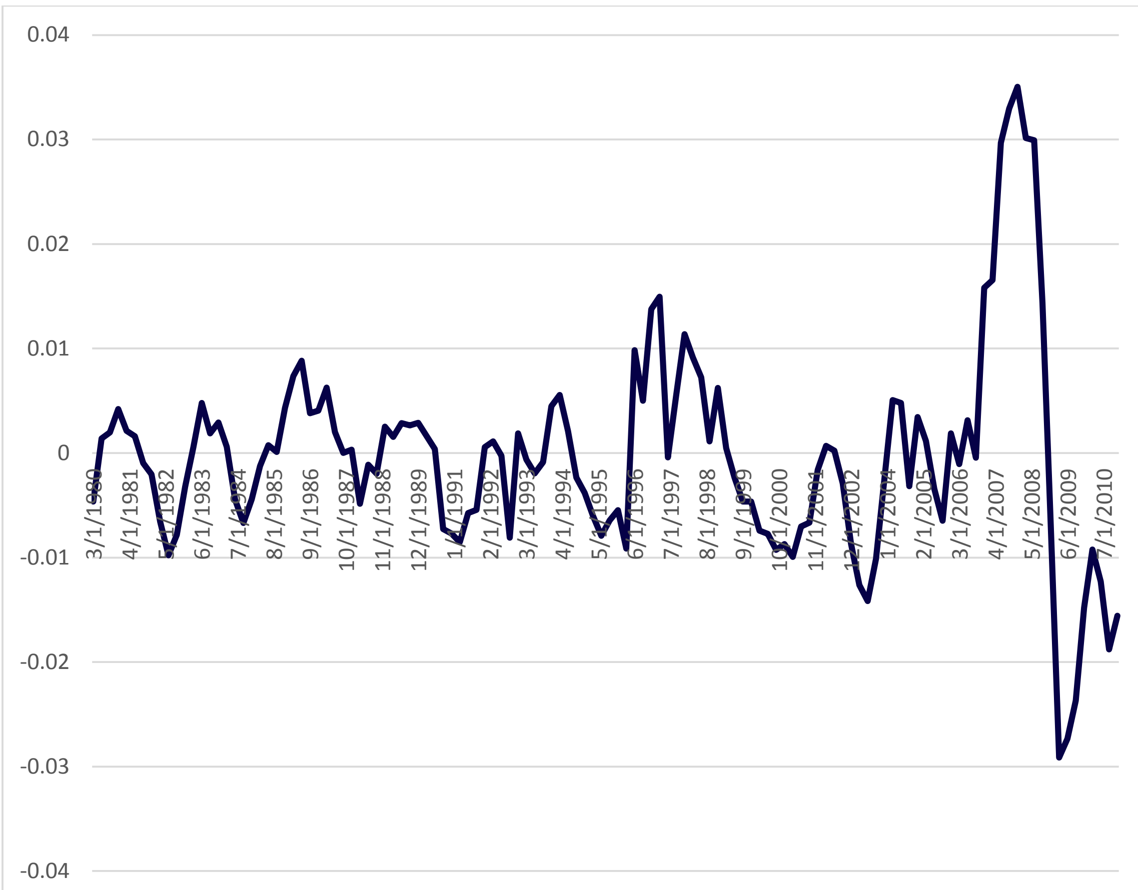

Figure 3.2 Time Series of equally-weighted abnormal institutional ownership. The figure plots the time series of abnormal institutional ownership for all common equity securities traded in the U.S. (share codes equal to 10 and 11). I calculate abnormal institutional ownership by de-trending institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. Institutional ownership is defined as the fraction of shares outstanding held by financial institutions. Abnormal institutional ownership for the whole market is calculated each quarter by equally-weighting each firm.

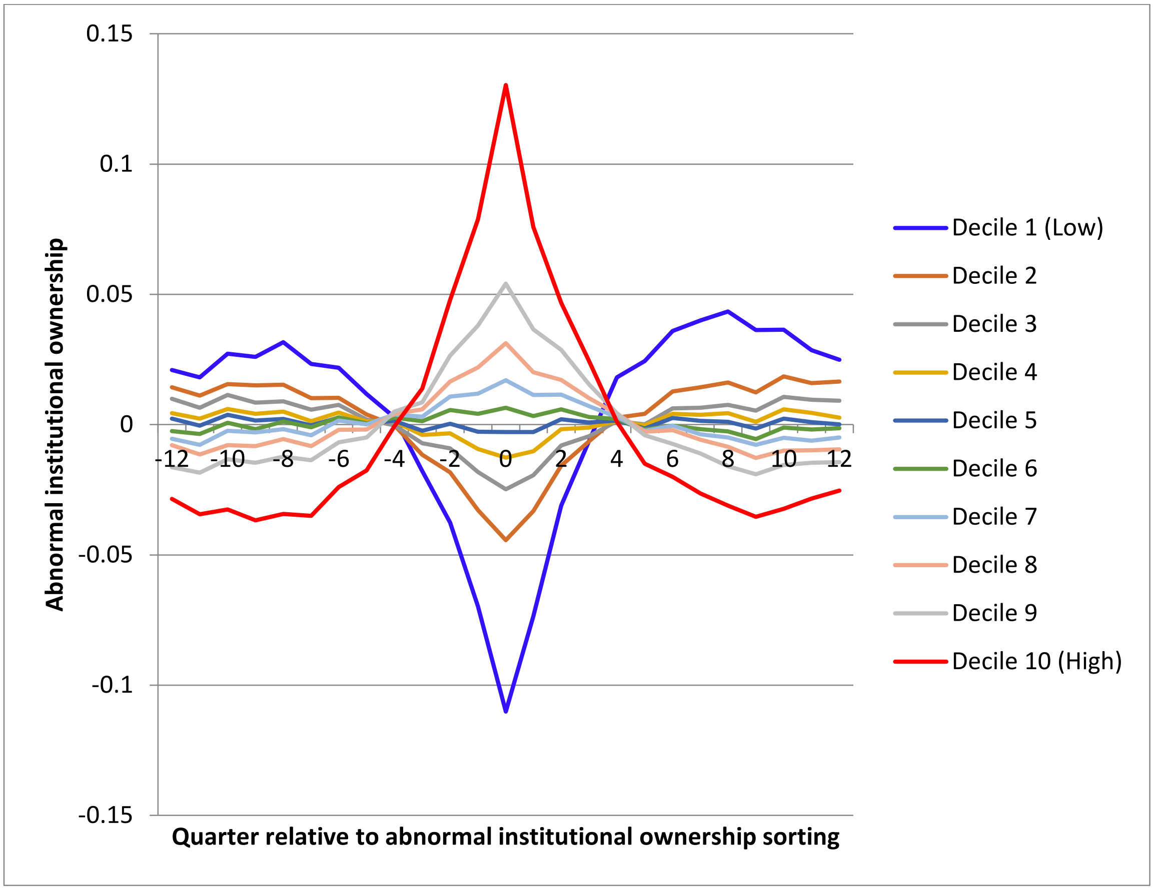

Figure 3.3 Mean abnormal institutional ownership in event time. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on abnormal institutional ownership. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. The table plots the equally-weighted level of abnormal institutional ownership for each of the 10 decile portfolios for the 12 quarters around the formation date.

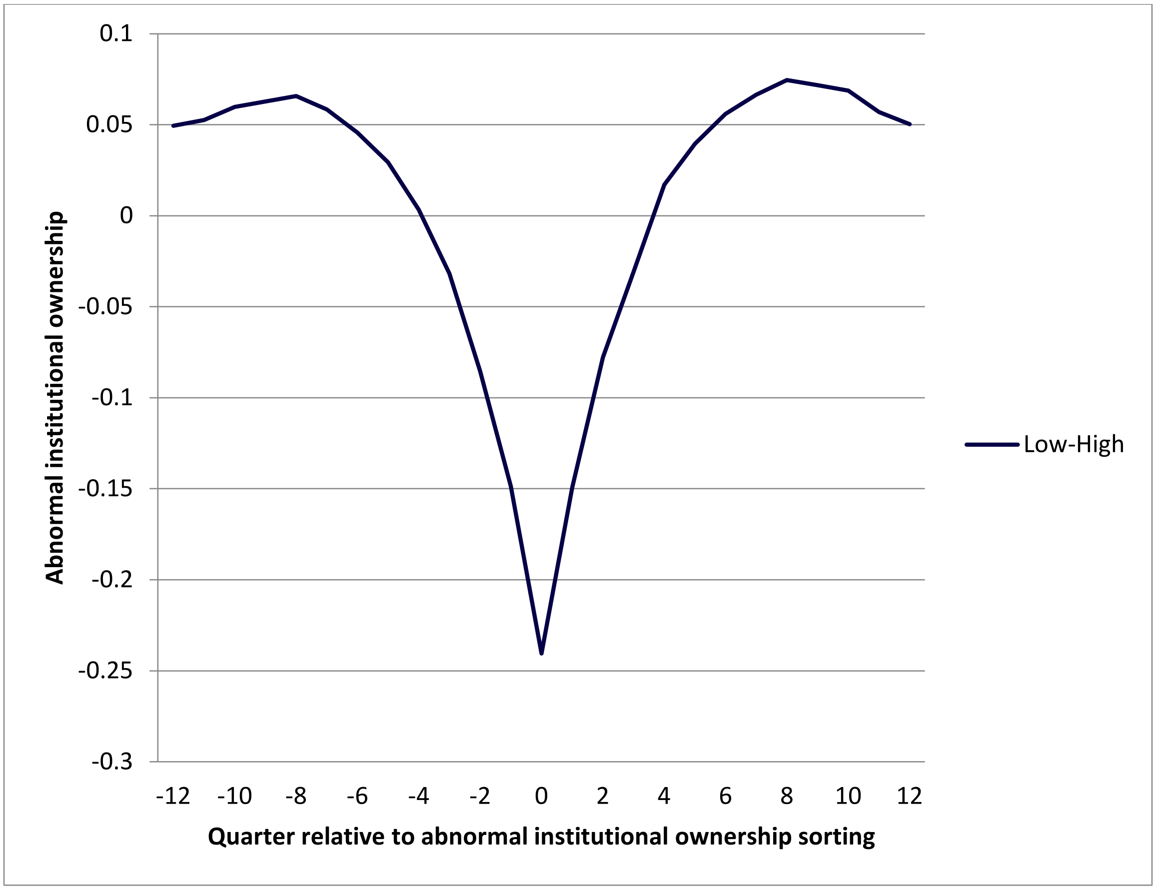

Figure 3.4. Mean difference in abnormal institutional ownership in event time. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on abnormal institutional ownership. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. The table plots the equally-weighted difference in abnormal institutional ownership for the low minus high abnormal institutional ownership portfolio for the 12 quarters around the formation date.

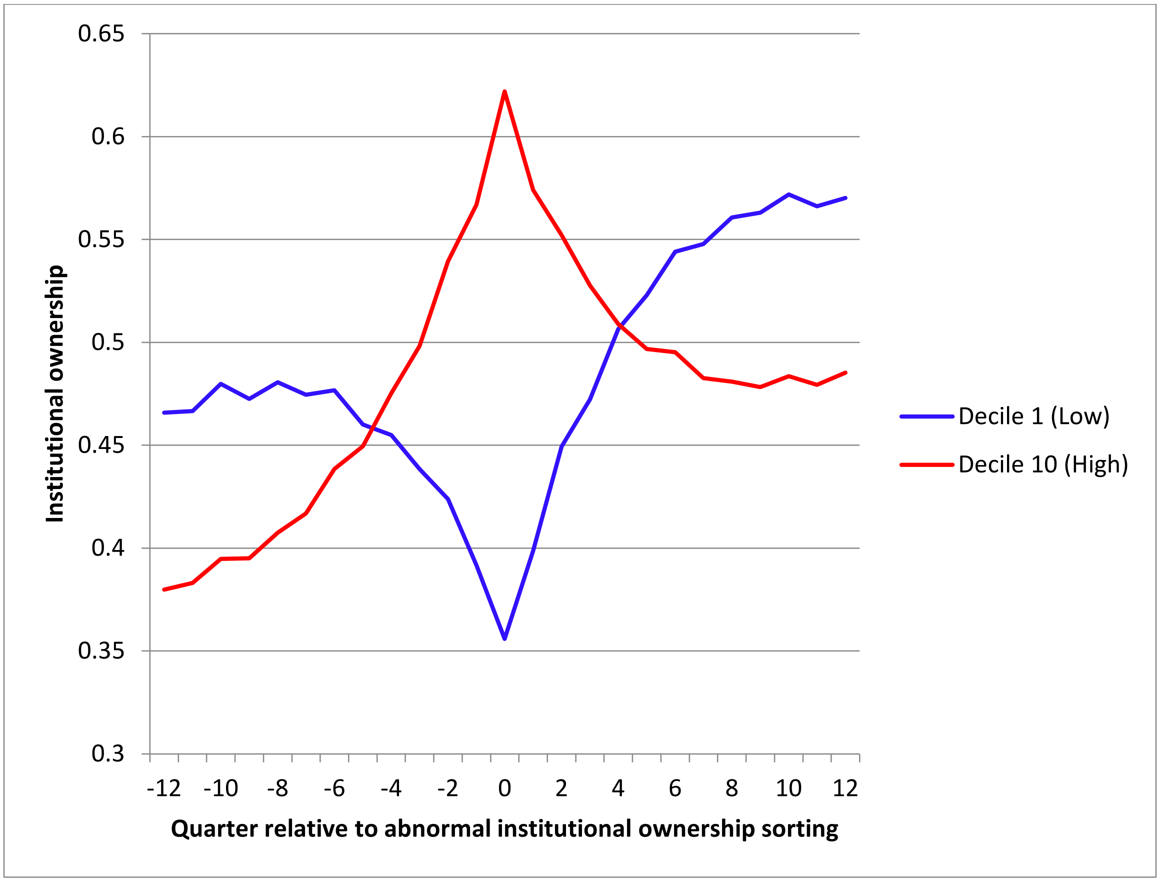

Figure 3.5 Mean institutional ownership in event time. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on abnormal institutional ownership. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. The table plots the equally-weighted level of institutional ownership for the low and high abnormal institutional ownership portfolios for the 12 quarters around the formation date.

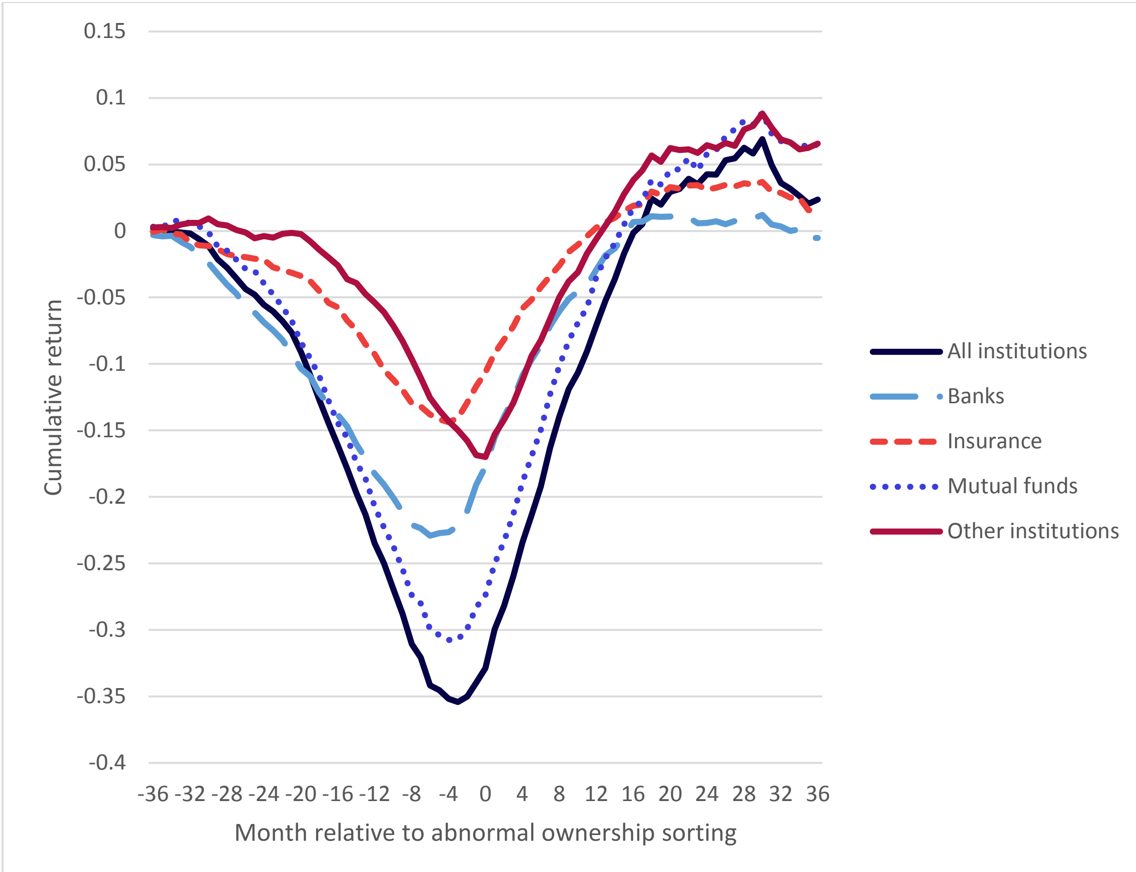

Figure 3.6 Cumulative return for abnormal ownership strategies in event time. Each June, firms are sorted on abnormal ownership and allocated to 1 of 10 decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than \$5 or greater than \$1,000. This figure plots the cross-sectional cumulative average return of the low-high portfolio for strategies formed using abnormal bank ownership, abnormal institutional ownership, abnormal insurance ownership, abnormal mutual fund ownership, and abnormal other ownership. Institution type is determined following the methodology of Lewellen (2011).

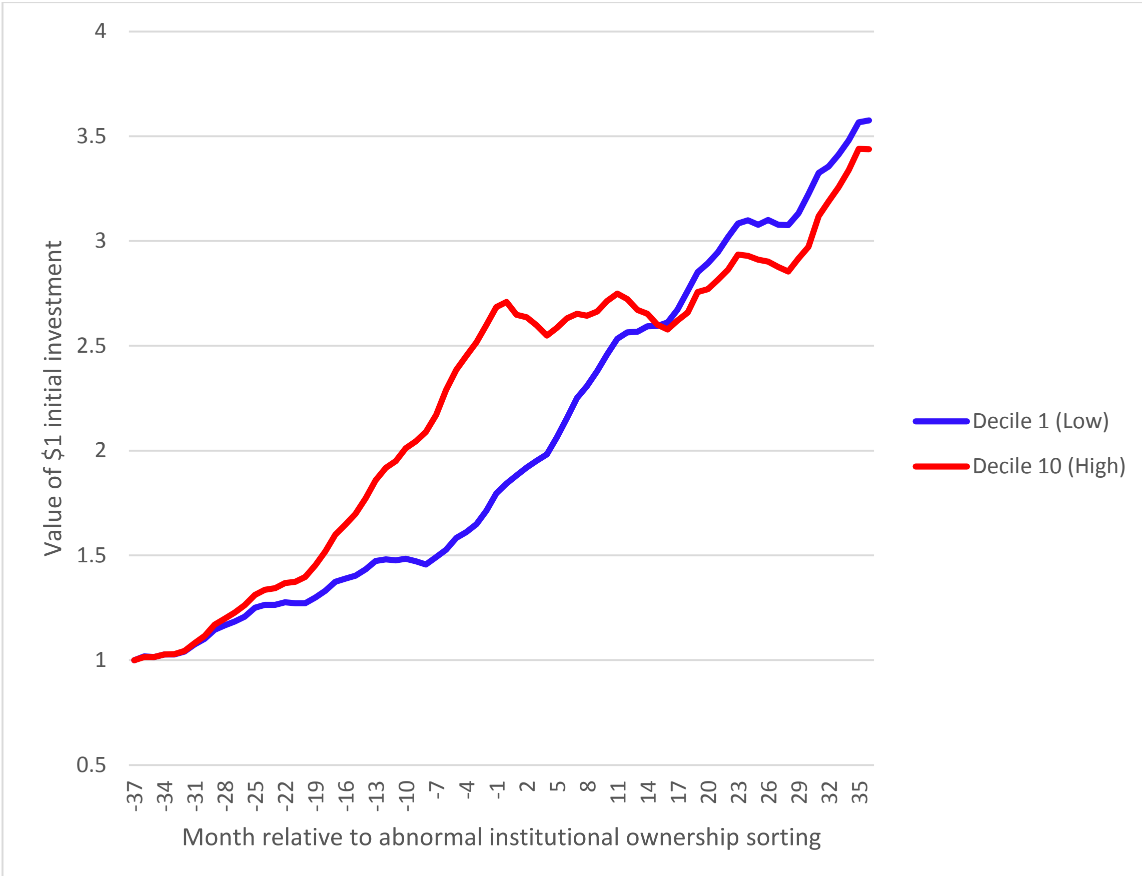

Figure 3.7 Value of $1 investment in abnormal institutional ownership portfolios in event time. Each June, firms are sorted on abnormal institutional ownership and allocated to decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than $5 or greater than $1,000. This figure plots the value of a $1 investment in the low and high decile portfolios for the 36 months surrounding the formation of the low-high abnormal institutional ownership portfolio.

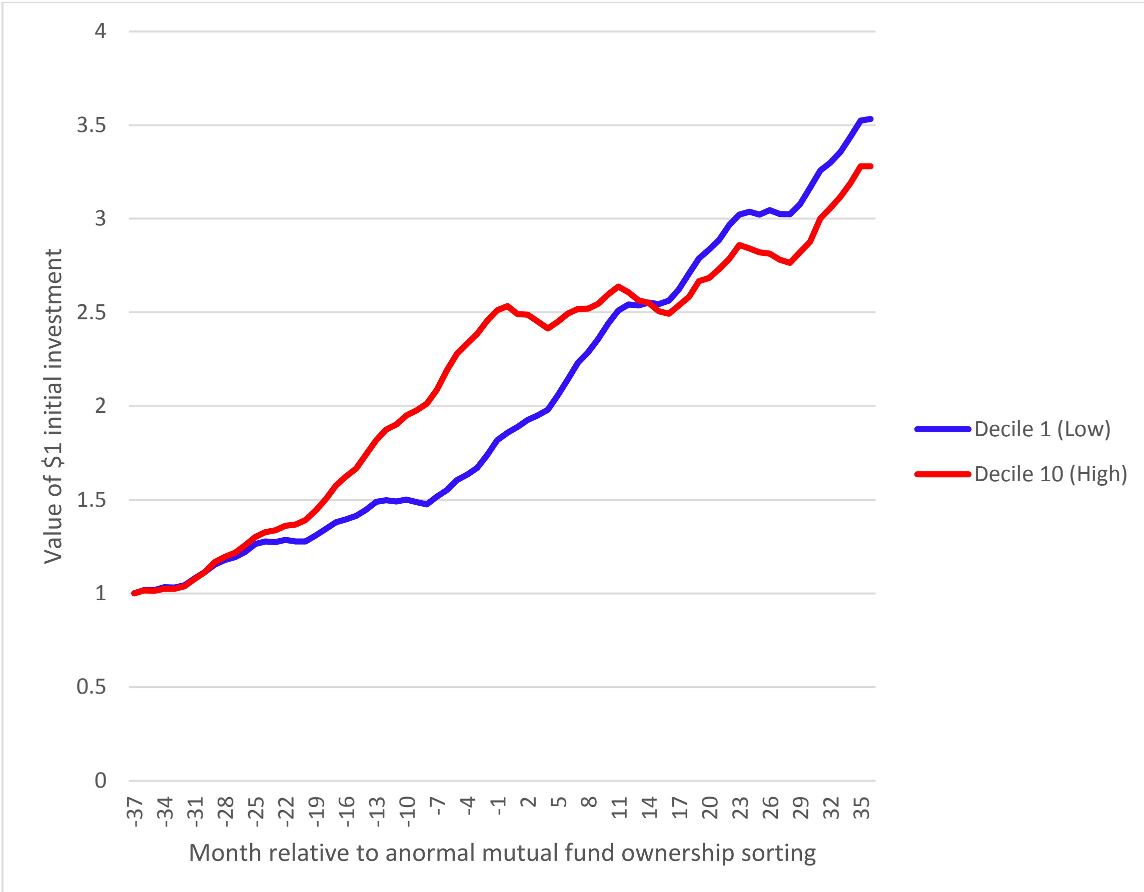

Figure 3.8 Value of $1 investment in abnormal mutual fund ownership portfolios in event time. Each June, firms are sorted on abnormal institutional ownership and allocated to decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than $5 or greater than $1,000. This figure plots the value of a $1 investment in the low and high decile portfolios for the 36 months surrounding the formation of the low-high abnormal institutional ownership portfolio.

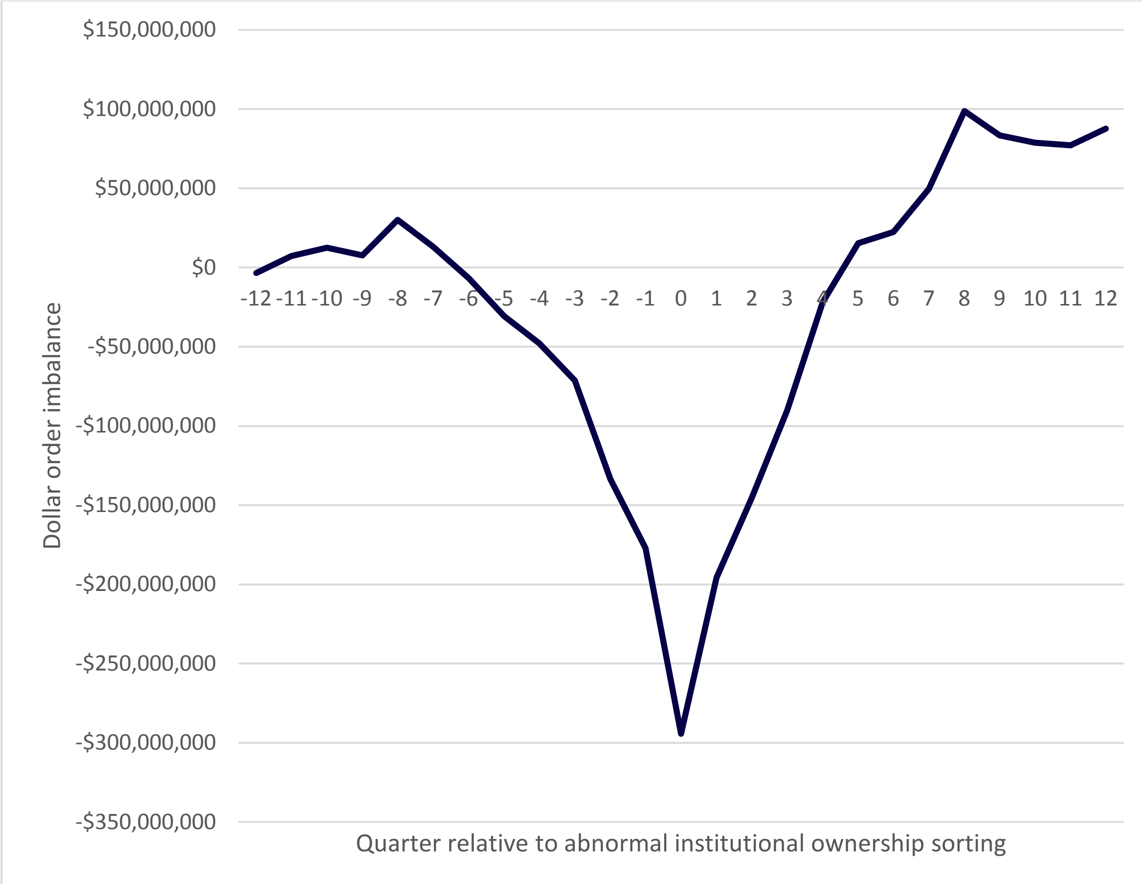

Figure 3.9 Cumulative dollar order imbalance in event time. This figure plots the cumulative average dollar net order imbalance for the 12 quarters surrounding the formation of the low-high abnormal institutional ownership portfolio. Each June, firms are sorted on abnormal institutional ownership and allocated to decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than $5 or greater than $1,000. For each quarter, I calculate the net dollar change in shares held by financial institutions for the low and high abnormal institutional ownership portfolios. Dollar change in shares held is defined as the average price over the quarter multiplied by the change in shares held. Dollar Order imbalance is then defined as the difference in the net dollar change in shares between the low and high abnormal institutional ownership portfolios.

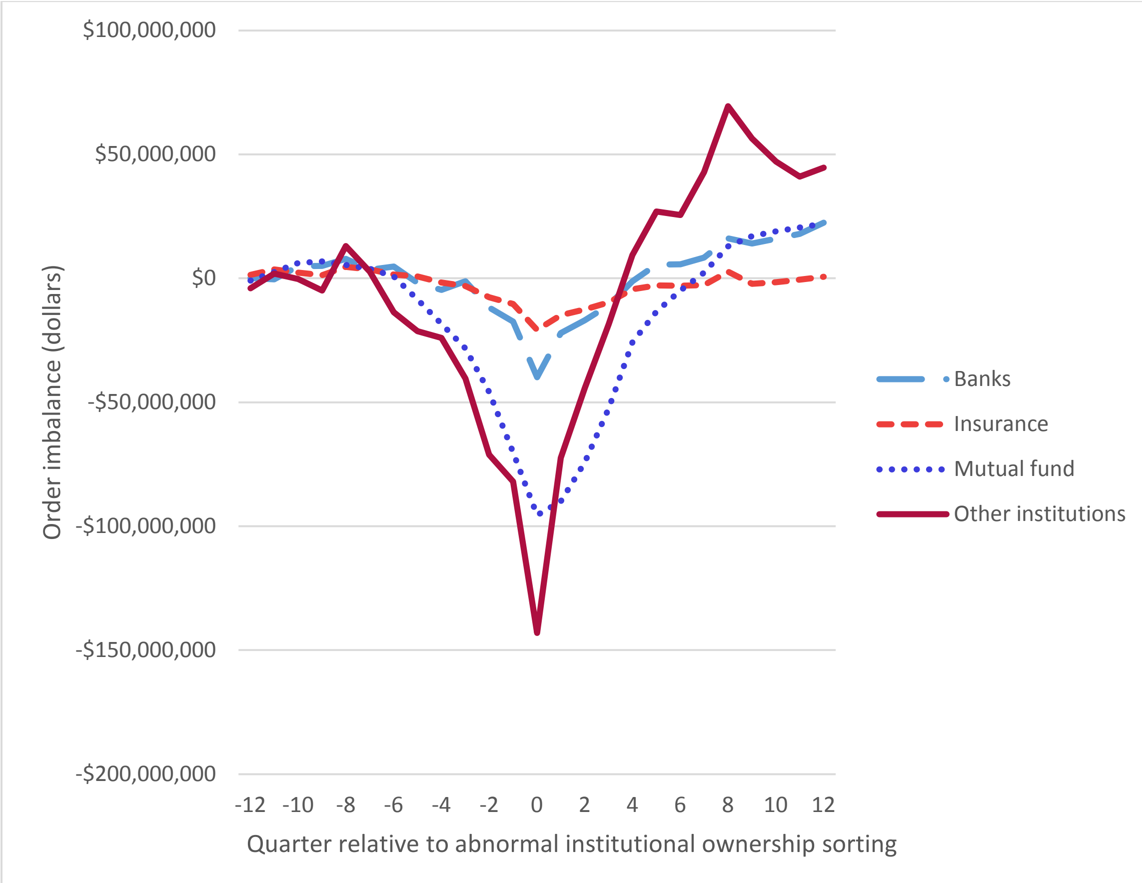

Figure 3.10 Cumulative order imbalance by institution type in event time for abnormal institutional ownership strategy. This figure plots the cumulative average net dollar order imbalance for the 12 quarters surrounding the formation of the low-high abnormal mutual fund ownership portfolio. Each June, firms are sorted on abnormal mutual fund ownership and allocated to decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than $5 or greater than $1,000. For each quarter, I calculate the net dollar change in shares held by financial institution type for the low and high abnormal institutional ownership portfolios. Order imbalance is then defined as the difference in the net change in shares between the low and high abnormal institutional ownership portfolios.

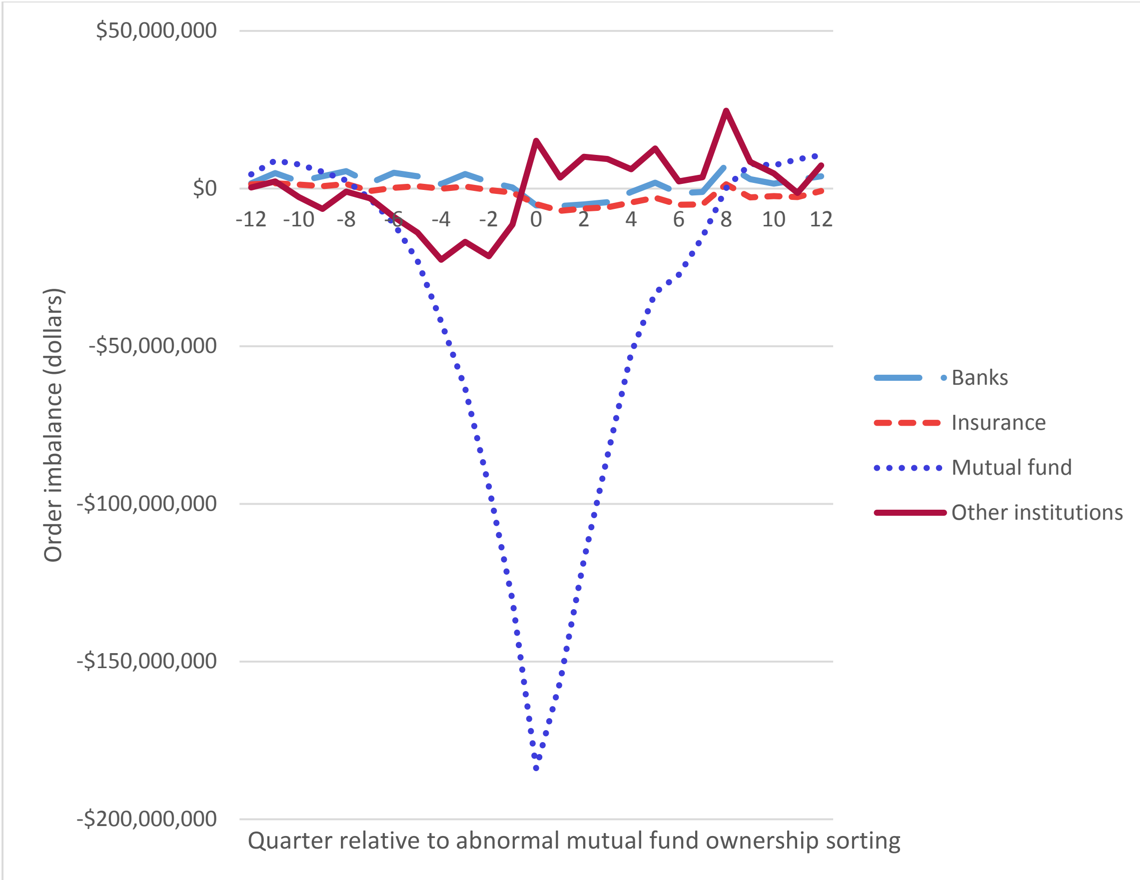

Figure 3.11. Cumulative dollar order imbalance by institution type in event time for abnormal mutual fund ownership strategy. This figure plots the cumulative average net dollar order imbalance for the 12 quarters surrounding the formation of the low-high abnormal mutual fund ownership portfolio. Each June, firms are sorted on abnormal mutual fund ownership and allocated to decile portfolios using NYSE breakpoints. At the time of formation, I exclude financials (SIC Codes 6000-6999), utilities (SIC Codes 4900-4999), and stocks with share prices less than $5 or greater than $1,000. For each quarter, I calculate the net dollar change in shares held by financial institution type for the low and high abnormal mutual fund ownership portfolios. Order imbalance is then defined as the difference in the net change in shares between the low and high abnormal mutual fund ownership portfolios.

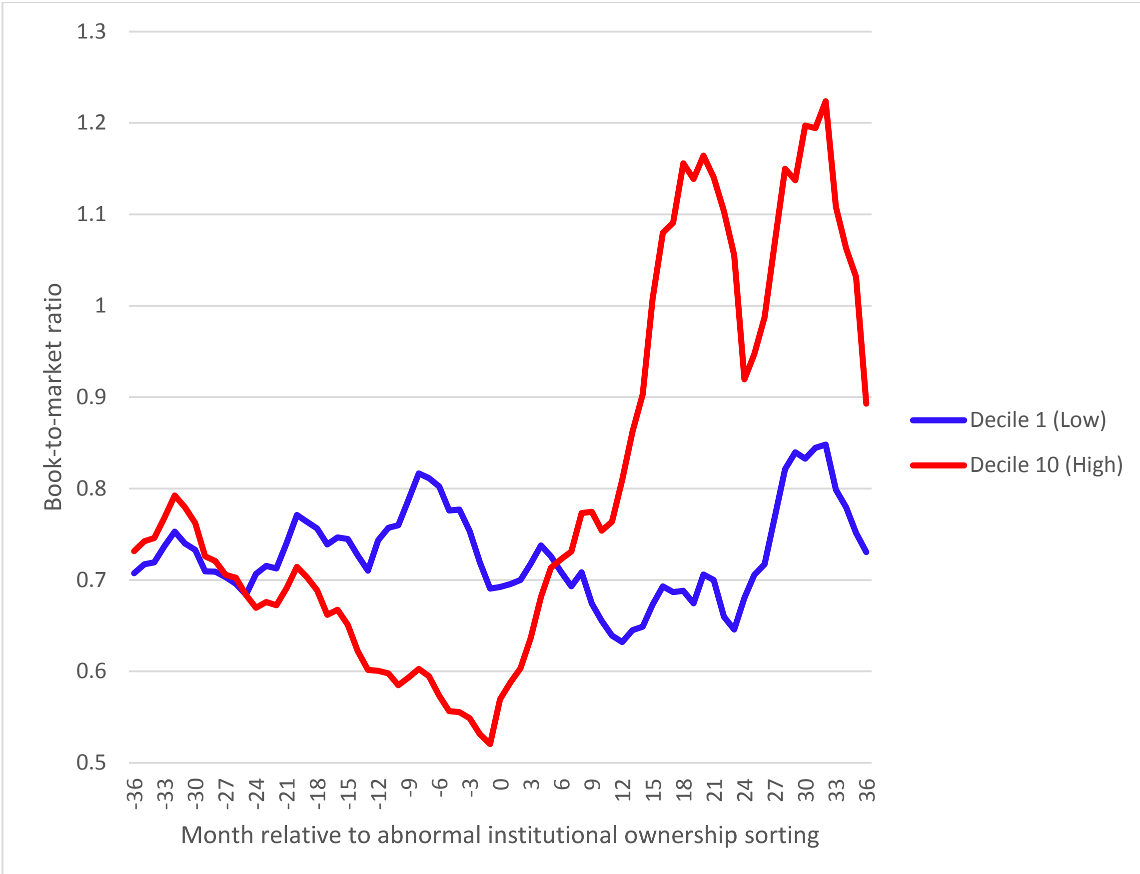

Figure 3.12. Mean book-to-market ratio in event time. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on abnormal institutional ownership. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600. The table plots the equally-weighted book-to-market ratio for the low and high abnormal institutional ownership portfolios for the 36 months around the formation date.

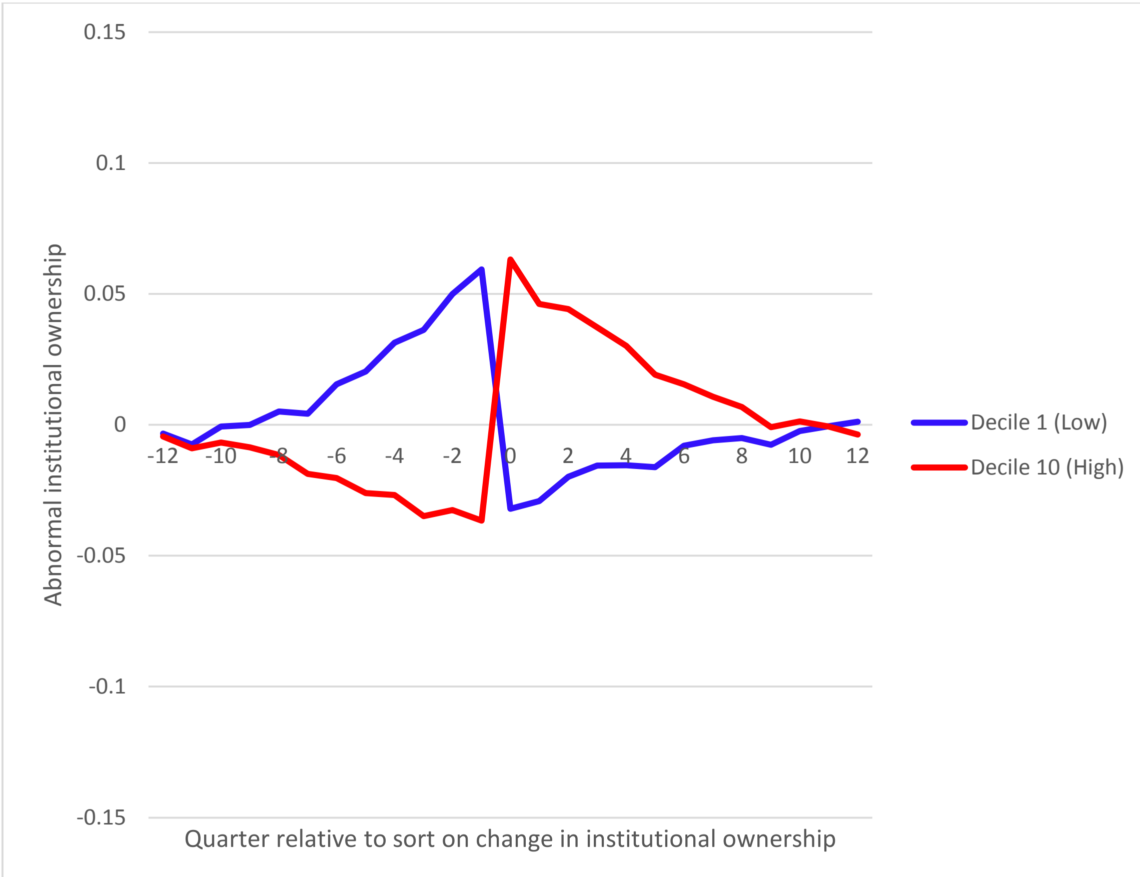

Figure 3.13 Mean abnormal institutional ownership in event time for change in institutional ownership portfolios. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on the quarterly change in institutional ownership. The table plots the equally-weighted level of abnormal institutional ownership for the 2 extreme decile portfolios for the 12 quarters around the formation date. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600.

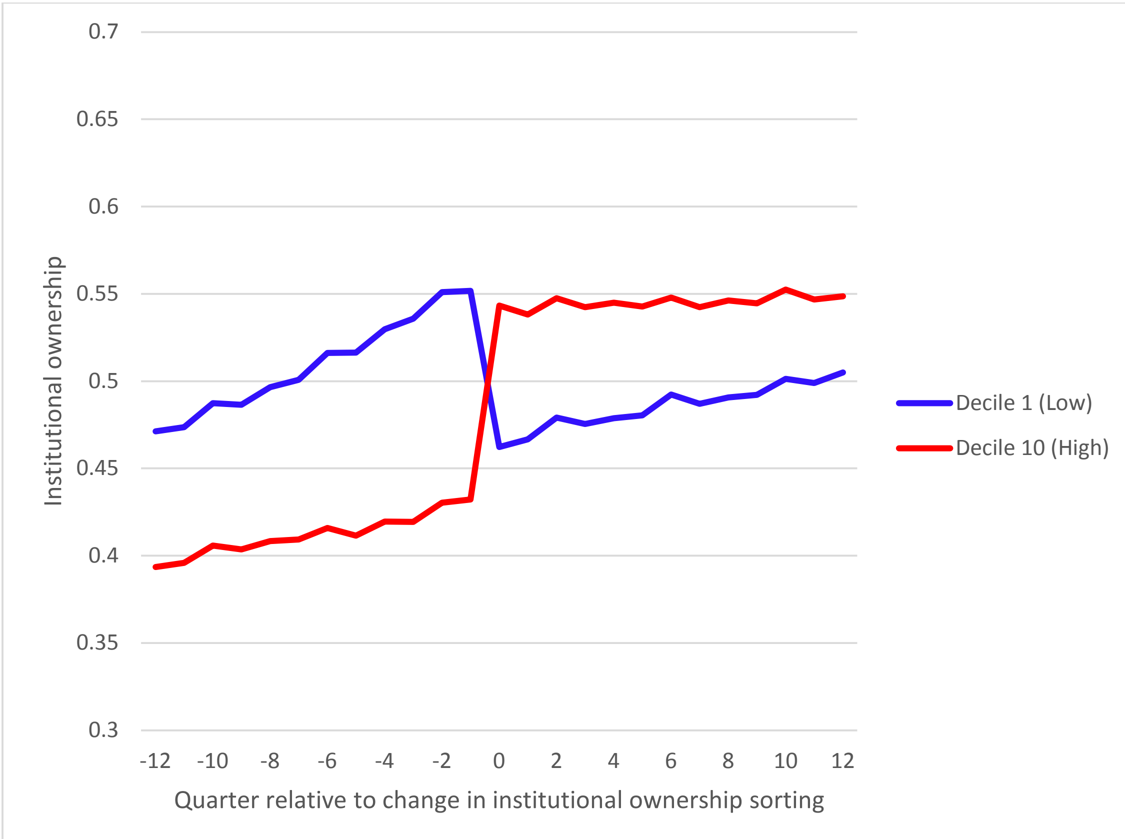

Figure 3.14 Mean institutional ownership in event time for change in institutional ownership portfolios. Each June from 1980 to 2010, firms are sorted into 10 decile portfolios on the quarterly change in institutional ownership. The table plots the equally-weighted level of institutional ownership for the 2 extreme decile portfolios for the 12 quarters around the formation date.

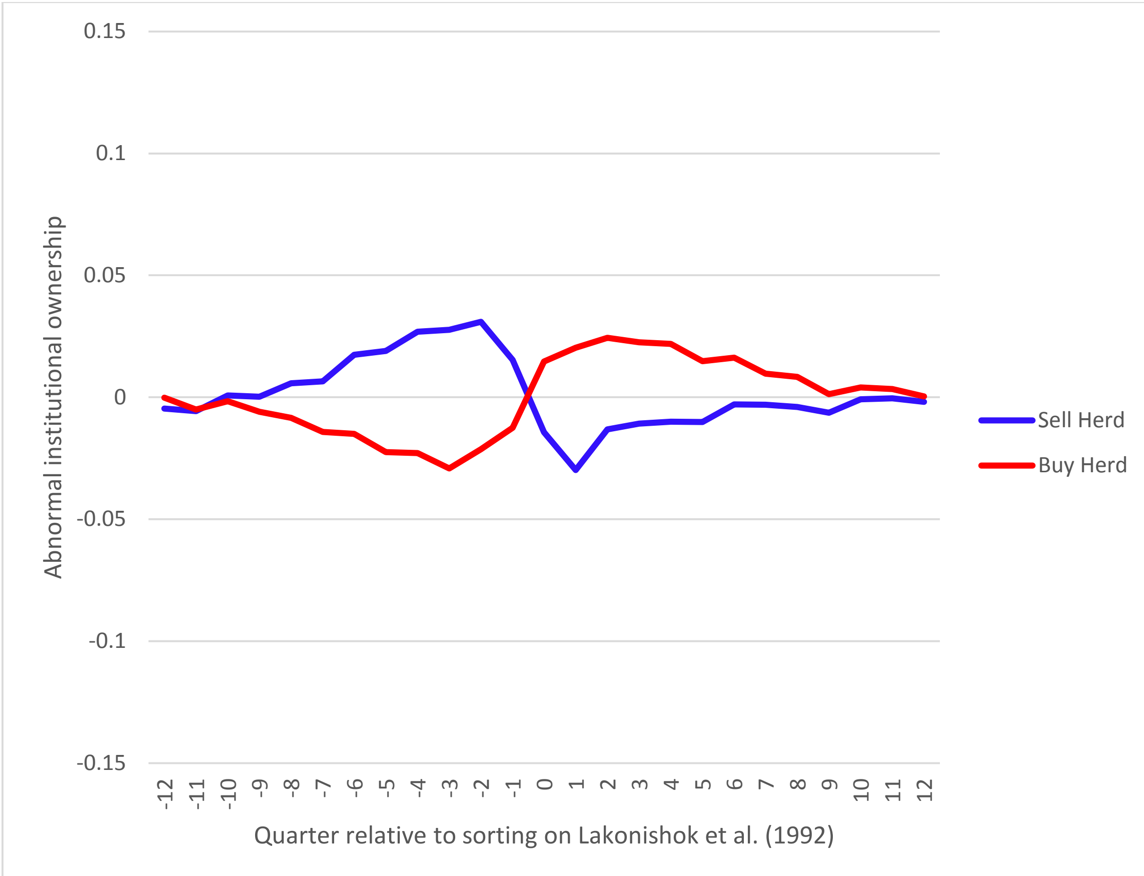

Figure 3.15 Mean abnormal institutional ownership in event time for herding portfolios. Each June from 1980 to 2010, firms are sorted into 10 mutual fund herding portfolios following the methodology of Wermers (1999). There are a total of 5 buy herd portfolios and 5 sell herd portfolios. The table plots the equally-weighted level of abnormal institutional ownership for strongest buy and sell herd portfolios for the 12 quarters around the formation date. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600.

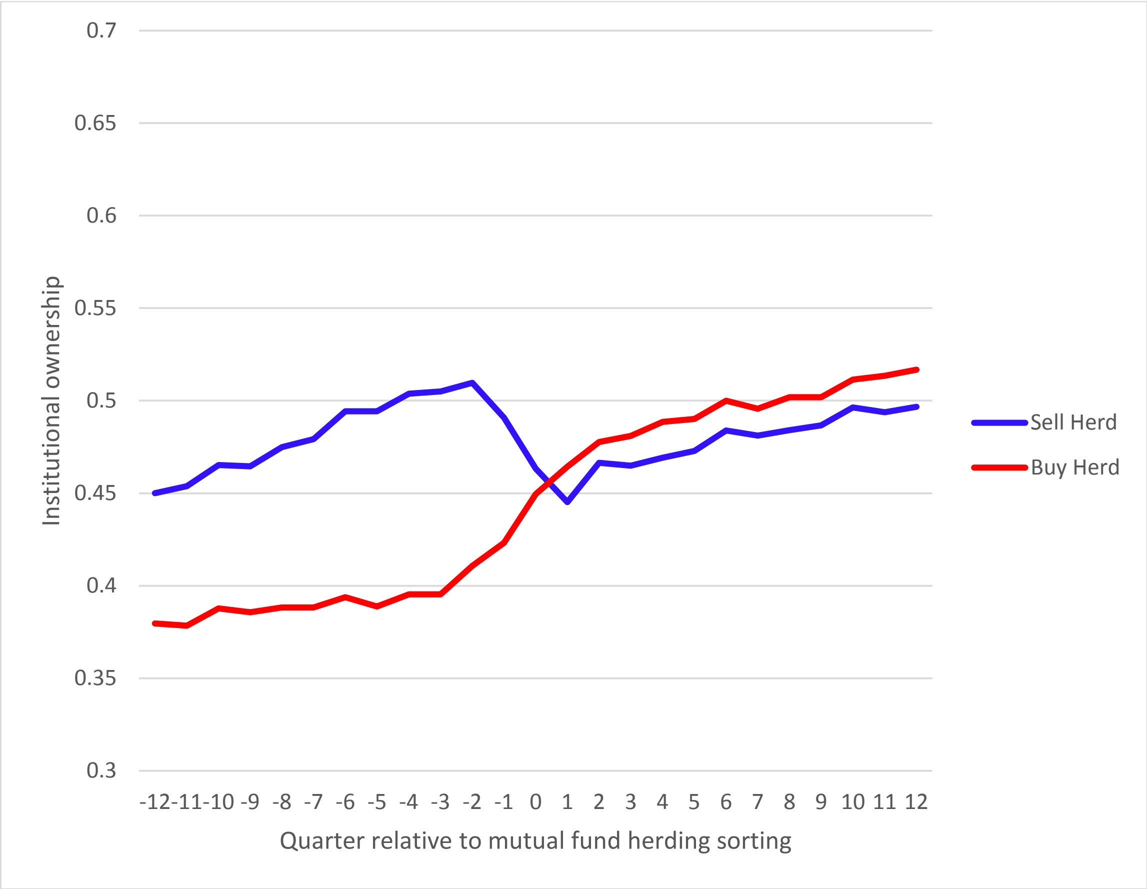

Figure 3.16 Mean institutional ownership in event time for herding portfolios. Each June from 1980 to 2010, firms are sorted into 10 mutual fund herding portfolios following the methodology of Wermers (1999). There are a total of 5 buy herd portfolios and 5 sell herd portfolios. The table plots the equally-weighted level of institutional ownership for strongest buy and sell herd portfolios for the 12 quarters around the formation date.

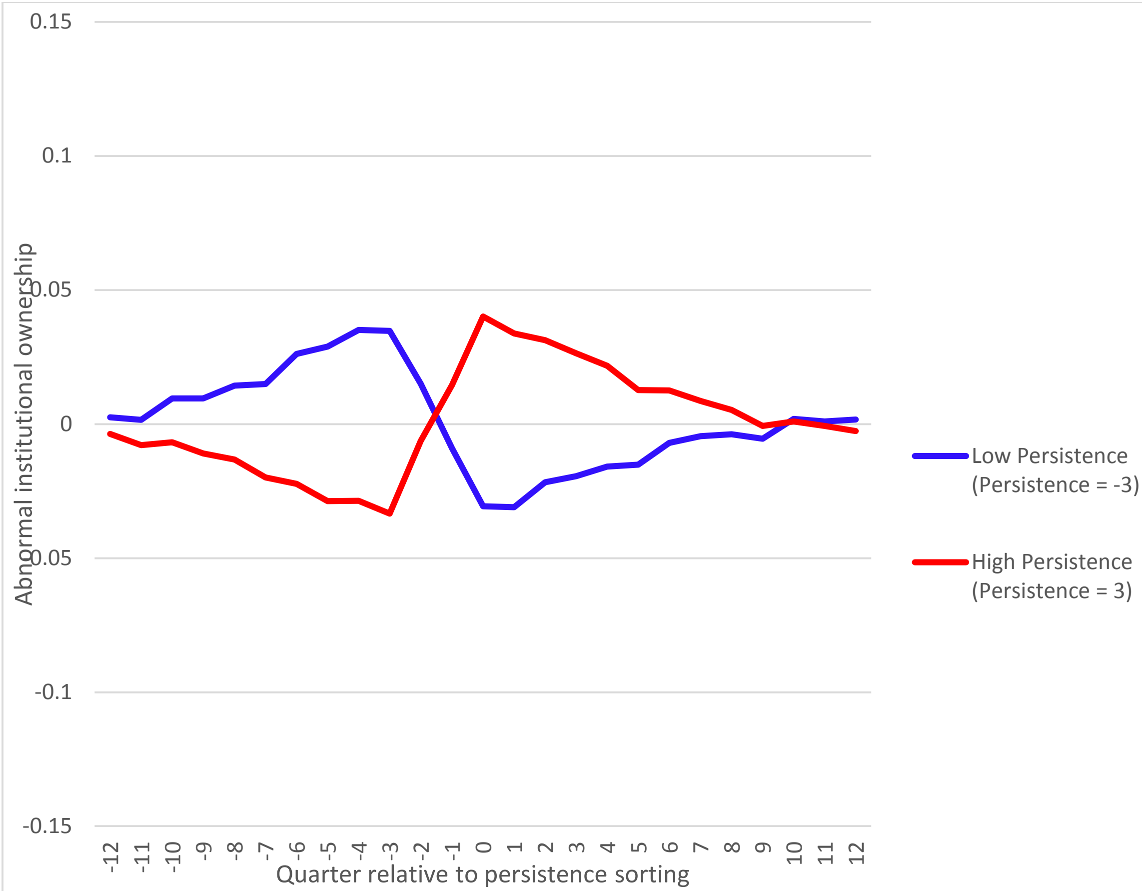

Figure 3.17 Mean abnormal institutional ownership in event time for persistence portfolios. Each June from 1980 to 2010, firms are sorted into 5 portfolios on the quarterly Dasgupta et al. (2011) persistence measure. The table plots the equally-weighted level of abnormal institutional ownership for low and high persistence portfolios for the 12 quarters around the formation date. Abnormal institutional ownership is defined as the residual institutional ownership after removing the trend from institutional ownership using the Hodrick-Prescott (1997) filter with λ equal to 1600.

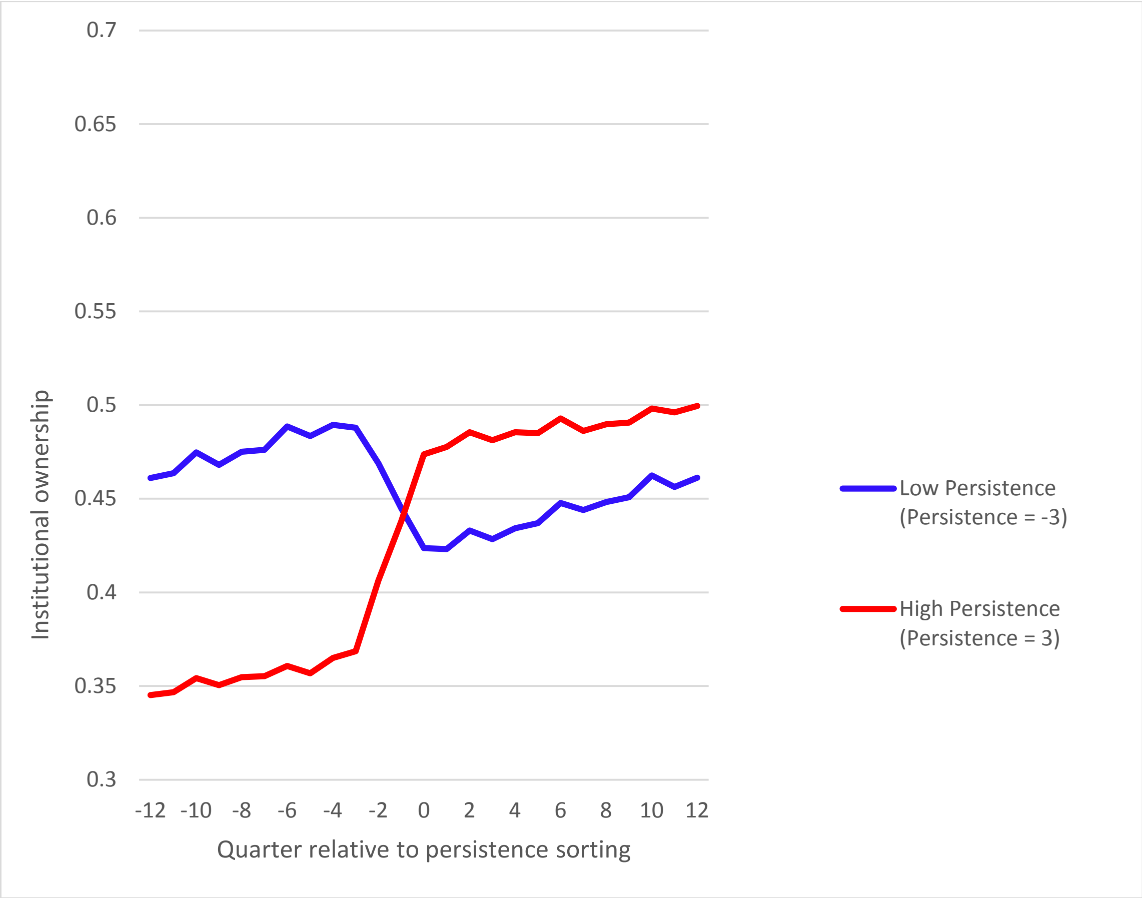

Figure 3.18 Mean institutional ownership in event time for persistence portfolios. Each June from 1980 to 2010, firms are sorted into 5 portfolios on the quarterly Dasgupta et al. (2011) persistence portfolios. The table plots the equally-weighted level of institutional ownership for the low and high persistence portfolios for the 12 quarters around the formation date.

APPENDIX A

TRADING STRATEGIES CONSIDERED IN THIS PAPER

A.1 Trading Strategies Description

I consider a total of 86 trading strategies. These strategies are constructed using data from CRSP, COMPUSTAT, and I/B/E/S. Typically, I construct the accounting-related strategies using annual data; however, where necessary I use quarterly data.

A.1.1 Trading Strategies 1–2: Accruals

I use 2 measures of accruals. The first measure is defined as in Sloan (1996) and the second measure is defined as in Fama and French (2008). Sloan (1996) finds that firms with low accruals have historically outperformed firms with high accruals.

A.1.2 Trading Strategy 3: Age

Baker and Wurgler (2006) study investor sentiment and firm age. They find that older firms outperform younger firms following years that ended with positive investor sentiment and younger firms outperform older firms following years that ended with negative investor sentiment. Following Baker and Wurgler (2006), I define firm age as the number of years since a firm first appeared in the CRSP database. I use the complete CRSP dataset, from 1925 onward, to construct this variable.

A.1.3 Trading Strategy 4: Analyst Coverage

A body of literature investigates analyst coverage and financial markets. James and Karceski (2006) investigate analyst recommendations and price targets and initial public offerings and find that poorly performing recent initial public offerings are given higher price targets and are more likely to receive strong buy recommendations. Yu (2008) investigates analyst coverage and earnings management and finds that more heavily followed firms manage their earnings less. Hong, Lim, and Stein (2000) finds that momentum strategies are stronger for firms with low analyst coverage. Other papers investigating analyst coverage include Chang, Dasgupta, and Hilary (2006); Cliff and Denis (2004); Irvine (2003); and McNichols and O'Brien (1997). Based on this evidence it seems reasonable to form portfolios on analyst coverage. I define analyst coverage as the number of analysts providing annual earnings forecast for a firm. I place all firms that do not have any analyst coverage in the lowest decile portfolio. The remaining firms that have at least 1 analyst providing earnings estimates are placed in 1 of 9 portfolios. These portfolios are formed by grouping firms based on 11.1 percentile breakpoints (100%/9 portfolios).

A.1.4 Trading Strategies 5–6: Asset Growth

Cooper, Gulen, and Schill (2008) find that firms with low asset growth rates outperform firms with high asset growth rates. This relation was further examined in Fama and French (2008). In this study, I use 2 definitions for asset growth. The first definition is the year over year change in total assets divided by lagged total assets as in Cooper, Gulen, and Schill (2008). The second definition follows the definition given in Fama and French (2008).

A.1.5 Trading Strategies 7–9: Book-to-Market

Fama and French (1992, 1993) present evidence that book-to-market ratios are an important determinant of stock market returns. In this study I use 3 different measures of book-to-market ratios. The first measure follows the methodology of Fama and French (1993) and uses book equity for fiscal year *t-1* divided by market equity at the end of December of year *t-1* to form portfolios in year *t*. The second measure of book-to-market equity uses book equity for fiscal year *t-1* divided by market equity at time *t*. Thus if I am forming portfolios in June of year *y*, then the value of market equity used to calculate book-to-market ratios is market equity at the end of June of year *y*. The third measure of book-to-market follows the methodology of Chen, Novy-Marx, and Zhang (2011) and divides adjusted book equity for fiscal year *t-1* by market equity. Chen, Novy-Marx, and Zhang (2011) adjust book equity by adding 10% of the difference between market equity and book equity to the value of book equity. I exclude firms with negative book-equity.

A.1.6 Trading Strategy 10: Campbell Distress Risk

Campbell, Hilscher, and Szilagyi (2008) present evidence that firms with low failure probability have historically outperformed firms with high failure probability. In this paper, I calculate the Campbell, Hilscher, and Szilagyi (2008) distress measure following the methodology outlined in their paper.

A.1.7 Trading Strategies 11–12: Cash Flow-to-Market Equity

Lakonishok, Shleifer, and Vishny (1994) present evidence that high cash flow-to-market equity firms earn a higher return than firms with low cash flow-to-market equity firms. I use 2 definitions of cash flow-to-market equity. The first definition uses annual cash flow divided by June market equity. The second definition uses annual cash flow divided by market equity at the end of the formation month.

A.1.8 Trading Strategies 13–14: Combination

Stambaugh, Yu, and Yuan (2012) present results for a strategy that buys equal amounts in the long legs of 11 different trading strategies and sells equal amounts in the short legs of the same 11 trading strategies. The 11 different trading strategies in Stambaugh, Yu, and Yuan (2012) are Campbell, Hilscher, and Szilagyi's (2008) distress probability, Ohlson's (1980) O-Score, Daniel and Titman (2006) composite equity issuances, net stock issuances, accruals, net operating assets, momentum, gross profitability, asset growth, return on assets, and investment-to-assets. I construct portfolio returns following this strategy as well as another strategy that combines equal amounts of the portfolio returns from trading on the 84 different trading strategies, excluding the 11 variable combination strategy.

A.1.9 Trading Strategy 15: Credit Rating

Avramov et al. (2012) investigate credit risk and other financial anomalies. They find that high credit rating firms (i.e., A+ rated firms) have a higher CAPM alpha than low credit rating firms (i.e., D rated firms). I use the firm's credit ratings from the COMPUSTAT database and construct portfolios following the methodology of Avramov et al. (2012). Additionally, Avramov et al. (2007) and Avramov et al. (2009) provide evidence that the returns to momentum and forecast dispersion strategies are concentrated in the lowest rated firms.

A.1.10 Trading Strategy 16: Daniel and Titman Composite Equity Issuances

Daniel and Titman (2006) present a new trading strategy, composite equity issuances, that measures the amount of equity the firm issues (or retires) in exchange for cash or services. They find that this variable forecasts returns. They find a negative relation between firm returns and their composite share issuances measure. I construct the composite share issuances measure using 5 years of data as in Daniel and Titman (2006).

A.1.11 Trading Strategy 17: Dividends-to-Book Equity

Baker and Wurgler (2006) use portfolios formed on dividends-to-book equity when investigating investor sentiment and stock market returns. They find that firms with positive dividends outperform firms with dividends less than or equal to 0 following years that ended with positive investor sentiment, and find the opposite relation following years that ended with negative investor sentiment. I use their definition of dividends-to-book equity: dividends per share at the ex-date multiplied by COMPUSTAT shares outstanding divided by book equity. I place all firms with dividends less than or equal to 0 in 1 portfolio and place all the dividend payers into decile portfolios.

A.1.12 Trading Strategies 18 and 19: Dividends-to-Price

Chung, Hung, and Yeh (2012) investigate the predictive power of investor sentiment for profitable trading strategies across different economic states, including a strategy that sorts firms on dividend yields. They find that non-dividend payers have historically earned a higher return than the highest decile of dividend payers, and that lagged investor sentiment predicts the long-short portfolio returns to a strategy that sorts firms on dividend yield. Dividend yield was also studied by Fama and French (1988), who found that dividend yields forecasts stock market returns. I use 2 different definitions of dividend yield. The first definition, following Kenneth French's website, gives dividend-to-price as the total dividends paid from July of year *t-1* to June of year *t* per dollar of equity in June of year *t*. The second definition calculates dividend yield as total dividends paid over the prior 12 months, inclusive of the current month, divided by the current share price. I place all firms with dividends less than or equal to 0 in the lowest decile portfolio.

A.1.13 Trading Strategy 20: Earnings-to-Book Equity

In Baker and Wurgler (2006), they argue that unprofitable firms are harder to value than profitable firms and should therefore be more influenced by investor sentiment. They find that following years ending with positive investor sentiment, profitable firms outperform unprofitable firms, and the opposite relation following years ending with negative investor sentiment. Following Baker and Wurgler (2006), I define earnings as income before extraordinary items plus income statement deferred taxes minus preferred dividends, and I define book equity as shareholders' equity plus balance sheet deferred taxes. If earnings are negative, I set earnings-to-book equity equal to 0. I place firms with earnings-to-book equity equal to 0 in 1 portfolio and all other firms with positive earnings-to-book equity values in 10 decile portfolios.

A.1.14 Trading Strategies 21–23: Earnings-to-Market Equity

Basu (1977) and Basu (1983) find that firms with high earnings-to-price ratios earn a higher return than firms with low earnings-to-price ratios. I use 3 definitions of earnings-to-market equity. The first definition uses earnings divided by June market equity. This variable is not updated for changes in firm size. The second definition updates the ratio each month to reflect each firm's current market capitalization. The third definition uses earnings as defined in Baker and Wurgler (2006) and is calculated annually in June of each year. Baker and Wurgler (2006) define earnings as income before extraordinary items plus income statement deferred taxes minus preferred dividends. I place all firms with negative earnings in the lowest decile portfolio.

A.1.15 Trading Strategies 24–25: External Finance

Baker and Wurgler (2006) investigate investor sentiment and external finance-to-assets. They find that decile portfolios formed on external finance usually have higher returns following years in which investor sentiment was negative at year end than in years in which investor sentiment was positive at year end. I use the definition of external finance given in Baker and Wurgler (2006): change in assets minus change in retained earnings all divided by total assets. I calculate this variable using 2 variations. The first variation calculates external finance using 1-year changes in assets and retained earnings and the second variation calculates external finance using 5-year changes in assets and retained earnings.

A.1.16 Trading Strategy 26: Firm Size

Banz (1981) and Fama and French (1992, 1993) find that small capitalization stocks have outperformed large capitalization stocks. I define firm size as share price multiplied by common shares outstanding (from CRSP). Firm size is updated each month to reflect the most recent share price and shares outstanding.

A.1.17 Trading Strategy 27: Forecast Dispersion

Diether, Malloy, and Scherbina (2002) investigate analysts' earnings forecast dispersion and stock returns. They find that stocks with low forecast dispersion earn a higher return than stocks with high forecast dispersion. I calculate forecast dispersion as the standard deviation of analysts' quarterly earnings forecasts. Earnings forecasts are adjusted to reflect the number of shares outstanding at the time of the forecast. The forecast dispersion measure is calculated using only the most recent analysts' forecasts prior to the earnings announcement date.

A.1.18 Trading Strategy 28: Gross Profits

Novy-Marx (2012b) studies firm profitability using gross profits-to-assets and the cross section of returns. He finds that more profitable firms outperform less profitable firms. Novy-Marx (2012b) defines profitability as total revenue less cost of goods sold divided by total assets. I use this definition (also used in Stambaugh, Yu, and Yuan (2012)) as the measure of gross profits.

A.1.19 Trading Strategies 29–30: Idiosyncratic Risk

Ang et al. (2006, 2009) investigate idiosyncratic risk and stock returns. They find that stocks with low idiosyncratic risk earn a higher return than stocks with high idiosyncratic risk. I follow the methodology of Ang et al. (2009) and calculate idiosyncratic risk as the standard deviation of the residuals from a monthly regression of daily excess returns on the Fama and French (1993) three-factor model. Excess returns are calculated as the difference between firm returns and the risk-free rate (the 1-month Treasury bill rate). I also estimate idiosyncratic risk using the standard deviation of the residuals from a monthly regression of daily excess returns on the 4 Carhart (1997) factors.

A.1.20 Trading Strategies 31–34: Illiquidity

In Amihud (2002), the author proposes an illiquidity measure called ILLIQ. This measure is calculated as the average daily ratio of absolute stock returns to dollar volume. Amihud (2002) finds that there is an illiquidity premium. Thus firms with high illiquidity are expected to earn a higher return than firms with low illiquidity. Asparouhova, Bessembinder, and Kalcheva (2010) find a positive and statistically significant relation between Amihud's ILLIQ measure and NYSE and Amex returns. Following the methodology given in Amihud (2002), for each firm I calculate the ILLIQ measure using a rolling window and 1, 3, 6, or 12 months of data.

A.1.21 Trading Strategy 35: Intermediate Momentum

While most papers investigate price momentum using lagged 12-month returns (Jegadeesh and Titman (1993, 2001)), Novy-Marx (2012a) argues that it is intermediate returns that predict future stock market returns. Novy-Marx (2012a) finds that the firms with high lagged 7- to 12-month returns outperform firms with low lagged 7- to 12-month returns. I define the intermediate momentum variable as the lagged 7- to 12-month compound return, with time 0 equal to the investment month.

A.1.22 Trading Strategies 36–40: Investments-to-Assets

Firms with high past investment have historically underperformed firms with low past investment (Titman, Wei, and Xie (2004) and Xing (2008)). Titman, Wei, and Xie (2004) define investment-to-assets as the ratio between capital expenditures scaled by sales and the average capital expenditures over the prior 3 years. Titman, Wei, and Xie (2004) then subtract 1 from this ratio. Stambaugh, Yu, and Yuan (2012) also use portfolios formed on investments-to-assets, but they define investments-to-assets as the annual change in gross property, plant and equipment plus the annual change in inventories scaled by the lagged book value of assets. I calculate 5 measures of investments-to-assets following the definitions of Titman, Wei, and Xie (2004) and Stambaugh, Yu, and Yuan (2012).

A.1.23 Trading Strategies 41–43: Liquidity Beta

Pástor and Stambaugh (2003) find that firms with high sensitivities to liquidity risk outperform firms with low sensitivities to liquidity risk. Following Pástor and Stambaugh (2003), I estimate liquidity betas by regressing excess returns on the aggregate liquidity factor and on the 3 Fama and French (1993) factors. Liquidity betas are estimated monthly using 12 months, 36 months, or 60 months of data.

A.1.24 Trading Strategies 44–46: Long Term Reversal

De Bondt and Thaler (1984) find that firms that had poor stock performance over the prior 3–5 years have better future performance than firms that had good stock performance over the prior 3–5 years. I investigate 3 different measures of long run firm performance: 24-month lagged compound return, 36-month lagged compound return, and 48-month lagged compound return.

A.1.25 Trading Strategies 47–49: Market Beta

Fama and French (1992) present evidence that firms with low market betas have historically outperformed firms with high market betas. I estimate market betas by regressing firm returns in excess of the 1-month Treasury bill rate on the Fama and French (1993) market factor. Market betas are estimated monthly using 12 months, 36 months, or 60 months of data.

A.1.26 Trading Strategies 50–51: Momentum

Firms with high returns over the past year have historically outperformed firms with low returns over the past year (Jegadeesh and Titman (1993, 2001)) over the following 6 to 12 months. I calculate momentum using 2 different definitions. The first definition, from Fama and French (2008), uses the compounded return between months *t-12* and *t-2*. The second definition, following Chordia and Shivakumar (2006), uses the compound return between months *t-7* and *t-2* (relative to the investment month). One month is skipped between formation and investment to control for the negative autocorrelation in firm returns documented in Jegadeesh (1990) and Novy-Marx (2012a). The 2 momentum variables are only calculated when there are no missing returns between the first formation month and the last formation month.

A.1.27 Trading Strategy 52: Net Operating Assets

Firms with high net operating assets have historically underperformed firms with low net operating assets (Hirshleifer et al. (2004)). I calculate net operating assets using the definition given in Hirshleifer et al. (2004): the difference between operating assets and operating liabilities scaled by lagged total assets.

A.1.28 Trading Strategy 53: Net Stock Issuances

Issuing firms have historically underperformed non-issuing firms (Ritter (1991), Loughran and Ritter (1995), and Ikenberry, Lakonishok, and Vermaelen (1995)). The relation between the returns of share issuers and non-issuers was further examined by size group in Fama and French (2008). I use the definition of net stock issuances given in Fama and French (2008): the log ratio of split adjusted shares to lagged split adjusted shares.

A.1.29 Trading Strategy 54–57: Ohlson's O-Score

Ohlson (1980) develops a measure of the likelihood a firm will go bankrupt. This measure is commonly referred to as Ohlson's O-score and was used by Griffin and Lemmon (2002) to study the relation between book-to-market ratios and distress risk. Griffin and Lemmon calculate Ohlson's O-score using the formula given in Ohlson's original paper. However, unlike Ohlson (1980), they do not adjust total assets for inflation. Additionally, Chen, Novy-Marx, and Zhang (2011) form portfolios by sorting firms on their O-score. However, unlike in Ohlson (1980) and Griffin and Lemmon (2002), they calculate Ohlson's O-score using a slightly different definition than given in those 2 papers. Chen, Novy-Marx, and Zhang (2011) calculate Ohlson's O-score using pretax income as the value for Ohlson's funds from operations variable, but it is not clear whether Ohlson calculated his O-score measure using this measure or using the Funds From Operations (FOPT) variable available on COMPUSTAT.

In this paper I calculate the O-score using pretax income because FOPT only has limited data availability. I calculate Ohlson's O-score using 4 different definitions. The first definition calculates the O-score measure following Griffin and Lemmon (2002). I calculate another measure of Ohlson's O-score following the definition given in Chen, Novy-Marx, and Zhang (2011). These 2 measures are calculated in June of year t and are used until May of year $t+1$. Unlike the prior 2 definitions, the last 2 O-score measures are calculated monthly to reflect changes in market equity, following the definition used in Chen, Novy-Marx, and Zhang (2011). They adjust total assets by 10% of the difference between market equity and book equity because of concerns that total assets might be too close to 0. However, sometimes market equity can be less than book equity. In this case the adjusted total assets would be less than the unadjusted total assets. I use one definition that adjusts total assets using 10% of the difference between market equity and book equity, and another definition that only makes an adjustment to total assets if market equity is greater than book equity. Generally, our results are weakened by the inclusion of 4 measures of Ohlson's (1980) O-score since previously Stambaugh, Yu, and Yuan (2012) showed that there is a relation between investor sentiment and the strategy that trades on O-score.

A.1.30 Trading Strategy 58: PPE-to-Assets

Baker and Wurgler (2006) study portfolios formed on the ratio of property, plant, and equipment-to-assets. They find that firms with high PPE-to-assets have higher returns than firms with low PPE-to-assets following years ending with positive investor sentiment and the opposite relation following years ending with negative investor sentiment. I calculate PPE-to-assets following Baker and Wurgler (2006), who define PPE-to-assets as total gross property, plant, and equipment divided by total assets. Firms with PPE-to-assets values that are less than or equal to 0 are placed in 1 portfolio and all other firms with positive PPE-to-assets values are placed in 10 decile portfolios.

A.1.31 Trading Strategy 59: Profit Margin

Haugen and Baker (2008) find that profit margin is an important predictor of future returns. Haugen and Baker (1996) find that firms with high expected returns have a larger profit margin than firms with low expected returns. I define profit margin as earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total revenue (REVT).

A.1.32 Trading Strategy 60: Profitability-to-Book

Fama and French (2008) study firm profitability using profitability-to-book ratios. Fama and French (2008) investigate whether a profitability premium can be found in different size groups, defining profitability as equity income minus preferred dividends plus deferred taxes divided by book equity. I use this definition of firm profitability.

A.1.33 Trading Strategy 61: R&D-to-Assets

In Baker and Wurgler (2006), they find that firms generally have higher average returns after years that ended with negative investor sentiment than years that ended with positive investor sentiment. Following Baker and Wurgler (2006), I define R&D-to-assets as research and development expense divided by total assets and set values of R&D-to-assets prior to 1972 as missing. Firms with R&D-to-assets values that are less than or equal to 0 are placed in 1 portfolio and all other firms with positive R&D-to-assets values are placed in 10 decile portfolios.

A.1.34 Trading Strategies 62–64: Return on Assets

Fama and French (2006) find that more profitable firms have higher expected returns, while Haugen and Baker (1996) find that firms with higher return on assets have a higher expected return. I use 3 different measures of return on assets. The first measure is calculated as income before extraordinary items divided by lagged total assets, the second measure is calculated as operating income after depreciation divided by lagged total assets, and the last measure is calculated as earnings before interest, taxes, depreciation, and amortization divided by lagged total assets. The first definition was used in Fama and French (2006). The second definition is similar to the definition used in Stambaugh, Yu, and Yuan (2012) who investigate investor sentiment and return on assets as well as other trading strategies.

A.1.35 Trading Strategies 65–66: Return on Equity

Chen, Novy-Marx, and Zhang (2011) propose a 3-factor model that includes a return on equity factor. Additionally, they find that a strategy that invests in high ROE firms and sells low ROE firms earns a positive return and has a positive alpha after regressing excess ROE returns on the 3 Fama and French (1993) factors. In Haugen and Baker (1996) the authors find that firms with higher return on equity have higher expected returns and in Haugen and Baker (2008) the authors find that return on equity is an important predictor of stock market returns. I use 2 measures of return on equity. The first definition of return on equity is calculated using earnings per share (Basic) excluding extraordinary items (EPSPX). The second definition is given in Chen, Novy-Marx, and Zhang (2011), except I use annual values for income before extraordinary items and book equity.

A.1.36 Trading Strategies 67–74: Return Variance

Haugen and Baker (1996) find that firms with high expected returns have lower volatility than firms with low expected returns, while Haugen and Baker (2008) find that the 24-month return variance is an important predictor of future returns. Following Haugen and Baker (1996, 2008), I calculate the total return variance for each stock as the squared log two-year return. This variance calculation is calculated using compounded monthly returns. I also calculate 7 other return variances measures calculated as the mean of squared daily returns over the prior 3, 6, 12, 24, 36, 48, or 60 months (inclusive of the current month). A similar type of definition of return variance was used in Campbell, Hilscher, and Szilagyi (2008) and Chen, Novy-Marx, and Zhang (2011). More recently, Baker and

Wurgler (2006) propose that stocks with high return variance are harder to value and harder to arbitrage than stocks with lower return variance. They find that when sentiment is high, high return variance stocks earn lower returns and when sentiment is low, they earn higher returns.

A.1.37 Trading Strategies 75–77: Sales Growth

Lakonishok, Shleifer, and Vishny (1994) find that firms with low sales growth outperform firms with high sales growth. Baker and Wurgler (2006) use sales growth as a proxy for whether a firm is hard-to-value. After sorting firms on past sales growth, they find that returns are generally higher in years that end with negative investor sentiment than in years that end with positive investor sentiment. Baker and Wurgler (2006) define sales growth as the 1-year change in net sales divided by prior-year net sales, while Lakonishok, Shleifer, and Vishny (1994) calculate annual sales growth rates for each firm and then rank firms by sales growth for years *t-1*, *t-2*, …, *t-5*. They then calculate a weighted average rank measure that gives a weight of 5 to the most recent year, a weight of 4 to the prior year, and so on. After calculating the weighted average sales rank for each firm, they form decile portfolios on this variable. I use 3 measures of sales growth. The first measure uses the weighted sales growth rank measure and portfolio formation methodology of Lakonishok, Shleifer, and Vishny (1994). The other 2 measures use the Baker and Wurgler (2006) definition of sales growth and are calculated as either the 1-year growth in sales or the 5-year growth in sales.

A.1.38 Trading Strategies 78-79: Sales-to-Market-Equity

I use 2 definitions of sales-to-market equity. Both definitions calculate sales-to-market equity as total revenues divided by market equity (firm size). The first definition is calculated using June market equity and the resulting value of sales-to-market equity is used from June of year *t* until May of year *t+1*. The second definition of sales-to-market equity is calculated monthly using the end of the month market equity. Haugen and Baker (1996) find that firms with high expected returns have a slightly higher sales-to-price ratio than firms with low expected returns, while Haugen and Baker (2008) also find a positive relation between sales-to-price and expected returns.

A.1.39 Trading Strategy 80: Share Turnover

A number of papers have found a statistically significant relation between firm returns and share turnover (Chordia, Subrahmanyam, and Anshuman (2001), Fu (2009), and Avramov, Chordia, Goyal (2006)). Additional evidence provided in Avramov, Chordia, and Goyal (2006) shows that for three-way sorted portfolios on prior return, illiquidity and turnover, there is generally a positive return difference between high turnover firms and low turnover firms. I define share turnover as the log of monthly share volume divided by number of shares outstanding. This definition of share turnover is similar to the definition used in Chordia, Subrahmanyam, and Anshuman (2001).

A.1.40 Trading Strategies 81–82: Short Run Momentum

Haugen and Baker (1996) find a positive relation between 3-month returns and expected returns. I use 2 definitions of 3-month returns. The first definition is the 3-month compound firm return inclusive of the formation month. The second definition lags each 3-month compound return by 1 month. This is done to control for the reversal documented by Jegadeesh (1990) and Lehmann (1990).

A.1.41 Trading Strategy 83: Short-term Reversal

Jegadeesh (1990) and Lehmann (1990) find reversal in short-term returns: Firms that performed poorly over the past week or month perform better in the following week or month. I measure short-term reversal as the 1-month return at the time of portfolio formation.

A.1.42 Trading Strategy 84: Standardized Unexpected Earnings

It has been well documented in the accounting literature that firms with positive earnings announcements outperform firms with negative earnings announcements (Ball and Brown (1968) and Bernard and Thomas (1989, 1990), among others). This phenomenon has been termed post-earnings-announcement drift. Typically, the relation between earnings and stock market returns is measured using standardized unexpected earnings (SUE). This measure is used in Bernard and Thomas (1989) and Chordia and Shivakumar (2006). Chordia and Shivakumar (2006) investigate price momentum and SUE. They define SUE as the difference between current earnings and earnings 4 quarters ago, divided by the standard deviation of this difference over the prior 8 quarters. I construct the SUE variable using this definition. The value of SUE is used for months' t to $t+2$ where t is the earnings announcement month.

A.1.43 Trading Strategies 85–86: Unexpected Earnings

Some scholars research post-earnings-announcement drift using analysts' forecasted earnings and actual earnings provided by I/B/E/S (Doyle, Lundholm, and Soliman (2006) and Livnat and Mendenhall (2006). I calculate unexpected earnings using 2 different definitions using data from I/B/E/S. The first definition of unexpected earnings is calculated as the difference between actual earnings reported in I/B/E/S and the median analysts' forecasted quarterly earnings, divided by the share price at the end of the month prior to the earnings announcement. The second definition of unexpected earnings is calculated with the same numerator as in the first definition. However, the denominator is the share price at the end of the month prior to portfolio formation. The value of unexpected earnings is used for months' *t* to *t+2* where *t* is the earnings announcement month.

Table A.1 List of the 86 different trading strategies considered in this paper.

Variable Number	Variable Name	Variable Short Name
1	Campbell Distress (from Campbell et al. (2008))	Campbell Distress
2	O-Score (Chen Novy-Marx Zhang (2011) Definition using Pre-tax income)	O-Score (1)
3	Net Stock Issues	Net Stock Issues
4	Daniel Titman (2006) Composite	Daniel Titman Composite
5	Accruals (Sloan (1996) Definition)	Accruals (1)
6	Net Operating Assets	Net Operating Assets
7	Momentum (Compound (t-12,t-2) Return)	Momentum (1)
8	Gross Profitability (from Novy-Marx (2012b))	Gross Profitability
9	Asset Growth (Cooper et al (2008) definition)	Asset Growth (1)
10	Return on Assets (Calculated using Income Before Extraordinary Items)	Return on Assets (1)
11	Investments to Assets (Stambaugh et al (2012) definition)	Investments to Assets (1)
12	Combination Strategy (Equally-weight strategies 1-11)	Combination Strategy (1)
13	Market Beta (60 month rolling window regression)	Market Beta (1)
14	Firm Size	Firm Size
15	Book-to-market (Fama French definition)	Book-to-market (1)
16	Liquidity Beta (60 month rolling window regression)	Liquidity Beta (1)
17	Accruals to Book (from Fama and French (2008))	Accruals (2)
18	Age (Baker and Wurgler (2006) definition in years)	Age
19	Analyst Coverage	Analyst Coverage
20	Asset Growth (Fama and French (2008) definition)	Asset Growth (2)
21	Book-to-market (Calculated annually using June Market equity)	Book-to-market (2)
22	Book-to-market (updated monthly)	Book-to-market (3)
23	Cash flow-to-market equity (calculated in June using June market equity)	Cash flow-to-market equity (1)
24	Cash flow-to-market equity (updated monthly)	Cash flow-to-market equity (2)
25	Credit Rating	Credit Rating
26	Dividends-to-book equity (Baker Wurgler (2006) definition)	Dividends-to-book equity
27	Dividends-to-price (Using Kenneth French online definition)	Dividends-to-price (1)
28	Dividends-to-price (updated monthly)	Dividends-to-price (2)
29	Positive earnings-to-book equity (Baker Wurgler (2006) definition)	Earnings-to-book equity
30	Earnings-to-market equity (Calculated annually in June)	Earnings-to-market equity (1)
31	Earnings-to-market equity (updated monthly using annual earnings)	Earnings-to-market equity (2)
32	Earnings-to-market equity (calculated annually using Baker Wurgler (2006) earnings definition)	Earnings-to-market equity (3)
33	External Finance (1 year change using Baker Wurgler (2006) definition)	External Finance (1)
34	External Finance (5 year change using Baker Wurgler (2006) definition)	External Finance (2)
35	Forecast Dispersion (Standard deviation of analysts' forecasts)	Forecast Dispersion
36	Idiosyncratic Risk (Ang et al. (2009) definition)	Idiosyncratic Risk (1)
37	Idiosyncratic Risk (Ang et al. (2009) definition calculated using residual from Carhart (1997) 4-factor model)	Idiosyncratic Risk (2)
38	Illiquidity (Amihud (2002) definition calculated using 1 month of daily data)	Illiquidity (1)
39	Illiquidity (Amihud (2002) definition calculated using 3 month of daily data)	Illiquidity (2)
40	Illiquidity (Amihud (2002) definition calculated using 6 month of daily data)	Illiquidity (3)

Table A.1 continued

Variable Number	Variable Name	Variable Short Name
41	Illiquidity (Amihud (2002) definition calculated using 12 month of daily data)	Illiquidity (4)
42	Intermediate Momentum (Lagged 6 month return used in Novy-Marx (2012a)	Intermediate Momentum
43	Investments to Assets (Avramov et al. (2012) definition and COMPUSTAT CAPEX)	Investments to Assets (2)
44	Investments to Assets (Avramov et al. (2012) definition using CAPEX calculated as Difference between changes in total assets and total liabilities)	Investments to Assets (3)
45	Investments to Assets (Titman et al. (2004) definition using COMPUSTAT CAPEX)	Investments to Assets (4)
46	Investments to Assets (Titman et al. (2004) definition using CAPEX calculated as Difference between annual change in total assets and annual change in total liabilities)	Investments to Assets (5)
47	Liquidity Beta (12 month rolling window regression)	Liquidity Beta (2)
48	Liquidity Beta (36 month rolling window regression)	Liquidity Beta (3)
49	Long-term Reversal (24 month compound return)	Long-term Reversal (1)
50	Long-term Reversal (36 month compound return)	Long-term Reversal (2)
51	Long-term Reversal (48 month compound return)	Long-term Reversal (3)
52	Market Beta (12 month rolling window regression)	Market Beta (2)
53	Market Beta (36 month rolling window regression)	Market Beta (3)
54	Momentum (Lag (t-6, t-1) return)	Momentum (2)
55	O-Score (Chen Novy-Marx Zhang Definition using pre-tax income calculated monthly using adjusted variables)	O-Score (5)
56	O-Score (Chen Novy-Marx Zhang Definition using pre-tax income, calculated monthly, do not adjust if book equity is less than market equity)	O-Score (6)
57	O-Score (Griffin and Lemmon (2002) definition using pre-tax income)	O-Score (8)
58	Profitability-to-book (Fama and French (2008) definition)	Profitability-to-book
59	Profit Margin	Profit Margin
60	PPE-to-Assets (Baker and Wurgler (2006) definition)	PPE-to-Assets
61	R & D-to-Assets (Baker and Wurgler (2006) definition	R&D-to-Assets
62	Return on Assets (Calculated using EBITDA)	Return on Assets (2)
63	Return on Assets (Calculated using Operating income after depreciation)	Return on Assets (3)
64	Return on Equity (Chen et al (2011) definition)	Return on Equity (1)
65	Return on Equity (calculated using Earnings per share (Basic) excluding extraordinary items)	Return on Equity (2)
66	Return Variance (3 month average of daily squared returns)	Return Variance (1)
67	Return Variance (6 month average of daily squared returns)	Return Variance (2)
68	Return Variance (12 month average of daily squared returns)	Return Variance (3)
69	Return Variance (24 month average of daily squared returns)	Return Variance (4)
70	Return Variance (36 month average of daily squared returns)	Return Variance (5)
71	Return Variance (48 month average of daily squared returns)	Return Variance (6)

Table A.1 continued

Variable Number	Variable Name	Variable Short Name
72	Return Variance (60 month average of daily squared returns)	Return Variance (7)
73	Return Variance (24 Month compound return squared)	Return Variance (8)
74	Sales Growth (1 Year sales growth using Baker and Wurgler (2006) definition)	Sales Growth (1)
75	Sales Growth (5 Year sales growth using Baker and Wurgler (2006) definition)	Sales Growth (2)
76	Sales Growth (5 Year Average rank from Lakonishok et al. (1994))	Sales Growth (3)
77	Sales to market equity (calculated using June market equity)	Sales-to-market equity (1)
78	Sales to market equity (updated monthly)	Sales-to-market equity (2)
79	Share Turnover (Natural log of monthly share turnover)	Share Turnover
80	Short-run Momentum (Compound 3 month return)	Short-run momentum (1)
81	Short-run Momentum (Lagged compound 3 month return)	Short-run momentum (2)
82	Short-term Reversal	Short-term Reversal
83	Standardized Unexpected Earnings (Chordia and Shivakumar (2006) definition)	SUE
84	Unexpected Earnings (Livnat and Mendhall (2006) definition; calculated at end of earnings announcement month using prior month's firm market equity in the denominator)	Unexpected Earnings (1)
85	Unexpected Earnings (Livnat and Mendhall (2006) definition; updated monthly using prior months market equity in the denominator)	Unexpected Earnings (2)
86	Combination Strategy (Equally-weight strategies 1-11 and 13-89)	Combination Strategy (2)

APPENDIX B

DESCRIPTIONS OF VARIABLES CONSIDERED

AND VALUATION MEASURES USED

B.1 Hard-to-Short Variable Descriptions

I consider a total of 33 different proxies for short sale constraints. These financial variables cover share price, firm size, liquidity, profitability, analyst coverage and forecast dispersion, volatility, idiosyncratic risk, short interest, transaction costs, and relative valuation. Below I list a detailed description of why each measure was chosen and how I define each measure.

B.1.1 Hard-to-Short Measure 1: Analyst Coverage

Diether and Werner (2011) find a negative relation between analyst coverage and loan fees. I define analyst coverage as the number of annual earnings forecasts provided by analysts from I/B/E/S. I only use each analyst's most recent forecast when constructing this measure.

B.1.2 Hard-to-Short Measure 2: Annual Mean Days to Cover

I calculate annual mean days to cover as the average of all observations over the prior year of the days to cover ratio that was calculated using the monthly average daily trading volume.

B.1.3 Hard-to-Short Measure 3: Annual Mean Dollar Short Interest

Annual mean dollar short interest is the average over the most recent year of all dollar short interest observations.

B.1.4 Hard-to-Short Measure 4: Annual Mean Short Interest

Similar to the short interest definition, I calculate annual mean short interest as the average value of all short interest observations for each firm over the prior year.

B.1.5 Hard-to-Short Measure 5: Book-to-Market Ratio

Diether and Werner (2011) find a negative relation between book-to-market ratios and short sale loan fees. Consistent with this result, D'Avolio (2002) finds that glamour stocks have higher loan fees than value stocks. I define book-to-market ratio as book equity divided by market equity using the definition used in Fama and French (1993).

B.1.6 Hard-to-Short Measure 6: Cash Flow to Assets

D'Avolio (2002) found that stocks with low cash flows have higher loan fees than stocks with high cash flows. Following D'Avolio (2002) I define cash flows as operating income after depreciation less accruals scaled by average total assets. I calculate average total assets as the average of beginning of the year and end of the year total assets. A similar definition was used in Sloan (1996).

B.1.7 Hard-to-Short Measure 7: Cash Flow to Book Equity

D'Avolio (2002) found that stocks with low cash flows have higher loan fees than stocks with high cash flows. Following D'Avolio (2002) I define cash flows as operating income after depreciation less accruals scaled by average book equity. I calculate average book equity as the average of beginning of the year and end of the year book equity, with book equity calculated using the Chen, Novy-Marx, and Zhang (2011) definition.

B.1.8 Hard-to-Short Measures 8–10: Corwin Schultz (2012) Bid-Ask Spread Measure

If illiquid firms are hard-to-short, then we would expect that firms with high transaction costs are hard-to-short. In this paper I use the Corwin Schultz (2012) bid-ask spread estimate as our measure of transaction costs. Corwin and Schultz (2012) find that their measure is highly correlated with effective spreads and generally performs as well as, if not better than, other transaction cost measures. I estimate the Corwin Schultz (2012) daily bid-ask spread measure using the SAS program that is kindly provided by Professor Corwin on his website. In this paper, I use 2 different bid-ask spread measures. The first measure is the monthly average of the Corwin Schultz (2012) daily bid-ask spread estimates and the second and third measures are the annual average of the Corwin Schultz (2012) daily bid-ask spread estimates. The first and third measures set negative bid-ask spread estimates to 0 prior to calculating the monthly or annual average bid-ask spreads.

B.1.9 Hard-to-Short Measure 11 and 12: Days to Cover

The days to cover ratio was previously used in Boehmer, Huszar, and Jordan (2010). They say that the days-to-cover ratio measures how long it will take for investors to cover their short positions in a security. In their paper, they present evidence that the median days to cover ratio and the aggregate amount of shorted shares are positively related and these measures have increased from 1988 to 2005 (Figure 1, page 83). I calculate 2 different days to cover variables. The first measure is defined as the number of shares sold short divided by the average daily volume over the current month and the second measure is defined as the number of shares sold short divided by the average daily volume over the prior year (inclusive of the current month). I expect that stocks with high days to cover ratios are harder-to-short than stocks with low days to cover ratios.

B.1.10 Hard-to-Short Measure 13: Dollar Short Interest

D'Avolio (2002) provides evidence that firms with high short interest have higher short sale loan fees. In a similar fashion to D'Avolio (2002), I calculate dollar short interest as number of shares sold short multiplied by end of month share price. I use the most recent short interest value in our analysis.

B.1.11 Hard-to-Short Measure 14: Firm Size

Previous literature has generally found that stocks with high loan fees are usually small market capitalization firms (D'Avolio (2002) and Diether and Werner (2011)). Firm size is calculated as common shares outstanding multiplied by share price.

B.1.12 Hard-to-Short Measure 15: Forecast Dispersion

D'Avolio (2002) found that stocks with higher forecast dispersion have higher loan fees than stocks with low analyst coverage. For the most part, a similar result was found in Diether and Werner (2011). I calculate forecast dispersion as the standard deviation of analysts' annual earnings forecasts. Earnings forecasts are adjusted to reflect the number of shares outstanding at the time of the forecast. Our forecast dispersion measure is calculated using only the most recent analysts' forecasts prior to the earnings announcement date.

B.1.13 Hard-to-Short Measure 16: Idiosyncratic Risk

The existing literature has argued that stocks with high idiosyncratic risk are harder to arbitrage because this risk cannot be offset by holding other securities (Pontiff (1996) and Wurgler and Zhuravskaya (2002). Additionally, idiosyncratic risk has been used as a measure of costly arbitrage (see for example Mashruwala et al. (2006), Kumar Lee (2006, and Lam and Wei (2011)). I follow the methodology of Ang, Hodrick, Xing, and Zhang (2009) and calculate idiosyncratic risk as the standard deviation of the residuals from a monthly regression of daily excess returns on the Fama and French (1993) 3-factor model. Excess returns are calculated as the difference between firm returns and the risk-free rate, the 1-month Treasury bill rate. I also estimate idiosyncratic risk using the standard deviation of the residuals from a monthly regression of daily excess returns on the Carhart (1997) 4 factors.

B.1.14 Hard-to-Short Measures 17 and 18: Illiquidity

D'Avolio (2002) provides evidence that illiquid firms are hard-to-short. Our measure of illiquidity is the Amihud (2002) measure. I use 2 measures of Amihud's (2002) illiquidity measure. The first measure is calculated using 1 month of daily data and the second measure is calculated using 12 months of daily data.

B.1.15 Hard-to-Short Measure 19: Institutional Ownership

D'Avolio (2002) provides evidence that firms with low institutional ownership are harder to short than firms with high institutional ownership. I define institutional ownership as the percentage of common shares outstanding held by financial institutions (as reported in 13F filings).

B.1.16 Hard-to-Short Measure 20: Liquidity Beta

Kumar and Lee (2006) suggest that stocks with high liquidity betas could be harder to arbitrage. Additionally, D'Avolio (2002) finds that less liquid stocks have higher short sale loan fees. Thus, it seems that stocks with high liquidity betas are harder-to-short. I calculate liquidity betas following the methodology given in Pastor and Stambaugh (2003) using 60 months of data. To be consistent with the trading strategies, I define hard-to-short stocks as those with low liquidity beta estimates.

B.1.17 Hard-to-Short Measure 21: Momentum

D'Avolio (2002) finds that stocks that have performed poorly in the past have slightly higher short sale loan fees than other stocks. Similarly, Diether and Werner (2011) find that there is a negative relation between lagged (12, 2) returns and loan fees. I define momentum as each firm's return over months *t-11* to *t-1* relative to the formation month.

B.1.18 Hard-to-Short Measure 22: Return on Assets

Based on the evidence in D'Avolio (2002), firms with low profitability should be harder to short than firms with high profitability. As an alternative to the cash flow measures, I use return on assets as an additional proxy for short sale loan fees. I calculate return on assets as income before extraordinary items scaled by average total assets.

B.1.19 Hard-to-Short Measure 23: Return on Equity

Following the reasoning in D'Avolio (2002) that firms with low cash flows are harder to value and thus are harder to short, it seems reasonable that firms with low return on equity would also be harder to short than firms with high return on equity. Furthermore, Chen et al. (2011) show that return on equity is an important firm characteristic. I define return on equity as income before extraordinary items scaled by average book value of equity. I calculate average book equity as the average of beginning of the year and end of the year book equity, with book equity calculated using the Chen, Novy-Marx, and Zhang

(2011) definition.

B.1.20 Hard-to-Short Measure 24: Share Price

D'Avolio (2002) finds that some hard to borrow stocks have stock prices below $5. Meanwhile, Diether and Werner (2011) provide evidence that NYSE and NASDAQ stocks below $5 have higher short sale loan fees and loan fees decrease as share price increases (see Diether and Werner (2011) Table III). Here, I define share price as the end of the month firm share price listed in CRSP.

B.1.21 Hard-to-Short Measure 25: Share Turnover

Diether and Werner (2011) found that short sales loan fees increase as share turnover increases and D'Avolio (2002) found that high turnover securities have higher loan fees than low turnover securities. Share turnover is calculated as monthly share volume divided by common shares outstanding.

B.1.22 Hard-to-Short Measure 26 and 27: Short-Term Reversal

Diether and Werner (2011) finds a negative relation between prior 1-month return and short sales loan fees. I use 2 different measures of stock price reversal. The first measure is each firm's return during the most recent month and the second measure is each firm's return from the previous month.

B.1.23 Hard-to-Short Measure 28: Short Interest

Diether and Werner (2011) find a positive relation between short interest and short sale loan fees. Similar to Diether and Werner (2011), I define short interest as number of shares sold short divided by number of common shares outstanding. I use the most recent short interest value in our analysis.

B.1.24 Hard-to-Short Measure 29 and 30: Volatility

In Diether and Werner (2011), the authors find a positive relation between stock volatility and short sale loan fees. I use 2 different measures of volatility. The first measure is the 3-month average of daily squared returns and the second measure is the 12-month average of daily squared returns.

B.1.25 Hard-to-Short Measure 31–33: Average Hard-to-Short Rank, Decile Rank, and Quintile Rank

Stambaugh, Yu, and Yuan (2012a) provide evidence that combining the information across variables can reduce the noise in each individual measure and create a more precise measure. With the goal of creating a less noisy and more precise measure of the difficulty to short a particular security I create 3 different aggregate measures of the difficulty to short a security. First I calculate the average hard-to-short variables rank. Each month I rank firms on each hard-to-short measure in descending order from hardest-to-short to easiest-to-short. I then calculate the average rank for each firm month observation. Next, I calculate the average hard-to-short deciles rank using NYSE breakpoints. Prior to imposing the price and industry filters, I allocate firms to 10 decile portfolios in ascending order from hardest-to-short to easiest to short using each of the 29 hard-to-short measures. Then for each firm month observation I calculate the average hard-to-short decile rank. Finally, I calculate the average hard-to-short quintile rank. Similar to the methodology used to calculate the average hard-to-short decile rank, I also calculate each firm's average hard-to-short quintile rank by allocating firms to 5 quintile portfolios.

B.2 Brief Description of Liquidity and Short Sale Constraint Measures

Amihud Illiquidity: Average 1-month Amihud (2002) illiquidity calculated using daily data. Amihud defines illiquidity as the average ratio of the daily absolute return to the dollar trading volume on that day.

Average Percentage of Zero Trading Days: Defined as the percentage of trading days within a month with 0 shares traded. A trading day is defined as any day with a non-missing daily return.

Corwin-Schultz Bid-ask Spread: Defined as the 1-month average daily bid-ask spread calculated using the Corwin-Schultz (2012) bid-ask spread estimator.

Daily Dollar Volume: Defined as the 1-month average daily dollar trading volume. Daily dollar trading volume is calculated each day by multiplying split-adjusted shares traded by the daily closing price.

Daily Share Turnover: Defined as the 1-month average daily share turnover, with daily share turnover defined as shares traded divided by shares outstanding.

Daily Volume: Defined as the 1-month average number of split-adjusted shares traded each day.

Pastor-Stambaugh Liquidity Beta: Defined as the liquidity beta estimated by regressing 60 months of excess returns on the Fama and French (1993) factors and on the Pastor and Stambaugh (2003) innovations in liquidity factor.

Average Return Variance: Defined as the 1-month average of squared daily returns, in percentages.

Forecast Dispersion: Defined as the standard deviation of analysts' annual earnings forecasts scaled by the absolute value of the mean earnings forecast. Earnings forecasts are adjusted to reflect the number of shares outstanding at the time of the forecast. The forecast dispersion measure is calculated using only the most recent analysts' forecasts prior to the earnings announcement date.

Idiosyncratic Risk: Following Ang et al. (2009), idiosyncratic risk is calculated as the standard deviation of the residuals from a monthly regression of daily excess returns on the Fama and French (1993) 3-factor model. Excess returns are calculated as the difference between firm returns and the risk-free rate, the 1-month Treasury bill rate.

Institutional Ownership: Defined as the total number of shares held (from 13F filings) by financial institutions divided by shares outstanding.

Short Interest: Total number of shares sold short divided by shares outstanding and multiplied by 100 to convert into percent form.

B.3 Brief Description of Valuation Measures

Analysts' Expected Return: Defined as the mean analysts' expected return. For each analyst providing a 1-year ahead price target, we calculate an expected return as (Price-Target*Shares outstanding – Current Firm Size)/Current Firm Size. Current firm size is defined to be current month-end share price multiplied by shares outstanding.

Average Recommendation: Defined as the mean recommendation provided by I/B/E/S analysts. Note that I/B/E/S uses the convention that 1= Strong Buy, 2= Buy, 3 = Hold, 4= Underperform, and 5 = Sell.

Book-to-Market Ratio: Defined as the book value of equity divided by the market value of equity. Book value of equity is calculated quarterly using the Fama and French (1992) definition. Book values are lagged 4 months to make sure that information was known by the market. Book-to-market ratios are updated monthly to reflect changes in market value of equity.

Compustat Intrinsic Value to Market Value of Equity Ratio: Defined as the median intrinsic value calculated using Compustat data divided by the current end-of-month market value of equity. COMPUSTAT intrinsic value is estimated using the residual income model assuming that each firm's current profitability is maintained in perpetuity. Thus, Compustat intrinsic value is defined as:

$$\text{Compustat intrinsic value} = BE_{t-1} + \frac{IB_t - r_E BE_{t-1}}{r_E} \quad (18)$$

where BE_{t-1} is the average book value of equity between times t-1 and t, IB_t is annual income before extraordinary items at time t, r_E is the cost of capital. Equation (1) is estimated using a total of 7 different cost of capitals: cost of capital estimated using 60 months of firm-level monthly returns and either the Fama and French (1993) 3-factor model or the Carhart (1997) 4-factor model, cost of capital estimated using 60 months of industry returns and either the Fama and French (1993) model or the Carhart (1997) model, or a discount rate of 8%, 10%, or 12%. Industry returns are calculated for each of the 48 Fama and French (1997) industries. Industries are determined using the Compustat industry code where available. Otherwise, the CRSP SIC Code is used. If a firm reports earnings before the release of its book value of equity then a synthetic book value of equity is constructed using the clean surplus relation, $BE_t = BE_{t-1} + IB_t - Div_t$. Intrinsic values less than 0 are set to missing. This methodology is closest to the methodology used in Ohlson (1995) and Bradshaw (2004).

I/B/E/S Intrinsic Value to Market Equity Ratio (1): Defined as the median intrinsic value calculated using 1-year ahead I/B/E/S annual earnings forecasts divided by the current market value of equity. Intrinsic value is calculated assuming that the forecasted profitability remains constant in perpetuity. I/B/E/S Intrinsic value is calculated using the following equation:

$$\text{Intrinsic Value} = BE_t + \frac{Forecasted\ IB_{t+1} - r_E BE_t}{r_E} \qquad (19)$$

where BE_t is the average book value of equity between periods *t-1* and *t*, Forecasted IB_{t+1} is the mean forecasted 1-year ahead expected earnings, and r_E is 1 of the 7 cost of capital estimates.

I/B/E/S Intrinsic Value to Market Equity Ratio (2): Defined as the median intrinsic value calculated using 1-year and 2-year ahead I/B/E/S annual earnings forecasts divided by the current market value of equity. Intrinsic value is calculated assuming that the current dividend payout rate and the forecasted profitability remains constant in perpetuity. I/B/E/S Intrinsic value is calculated using the following equation:

$$\text{Intrinsic Value} = BE_t + \frac{Forecasted\ IB_{t+1} - r_E BE_t}{(1+r_E)} + \frac{Forecasted\ IB_{t+2} - r_E BE_{t+1}}{(1+r_E) * r_E} \qquad (20)$$

where BE_t is the average book value of equity between periods *t-1* and *t*, Forecasted IB_{t+1} is the mean forecasted 1-year ahead expected earnings, Forecasted IB_{t+2} is the mean forecasted 2-year ahead expected earnings and r_E is 1 of the 7 cost of capital estimates. Intrinsic values less than 0 are set to missing.

I/B/E/S Intrinsic Value to Market Equity Ratio (3): Defined as the median I/B/E/S intrinsic value estimated using equations (1) and (2) divided by market value of equity.

Table B.1 Description of 50 variables used to construct 50 trading strategies. This table provides a brief description of the variables used to construct the 50 trading strategies. A more detailed description of these variables is given in Bulsiewicz (2013). The first 16 variables were used in Stambaugh et al. (2012b) and Bulsiewicz (2013) while the remaining 34 new variables were used in Bulsiewicz (2013). More information, including previous studies that used these variables, is given in Bulsiewicz (2013).

Panel A. Original financial variables

Variable Short Name	Definition
(1) Campbell Distress	Campbell distress risk calculated following Campbell et al. (2008) definition
(2) O-Score (1)	Ohlson's O-Score measure calculated using Chen Novy-Marx Zhang (2011) definition using Pre-tax income
(3) Net Stock Issues	log ratio of split adjusted shares to lagged split adjusted shares (from Fama and French (2008))
(4) Daniel Titman Composite	5 year log growth in market equity minus 5 year log return (from Daniel and Titman (2006))
(5) Accruals (1)	(change in current assets - change in cash - change in current liabilities - depreciation expense + change in short term debt + change in taxes payable)/average total assets (from Sloan (1996))
(6) Net Operating Assets	defined as the difference between operating assets and operating liabilities scaled by lagged total assets (as in Hirshleifer et al. (2004))
(7) Momentum (1)	Cumulative compound return from month t-12 to month t-2
(8) Gross Profitability	total revenue less cost of goods sold divided by total assets (from Novy-Marx (2012b))
(9) Asset Growth (1)	annual change in total assets divided by lagged total assets (from Cooper et al. (2008))
(10) Return on Assets (1)	Income before extraordinary items divided by lagged total assets (from Fama and French (2006))
(11) Investments to Assets (1)	annual change in gross property, plant and equipment plus the annual change in inventories scaled by the lagged book value of assets (Stambaugh et al (2012)
(12) Combination Strategy (1)	Combination Strategy from Stambaugh et al. (2012); Equally-weights strategies 1-1
(13) Market Beta (1)	regress monthly firm returns in excess of the one-month Treasury bill rate on the Fama and French (1993) market factor using a 60 month rolling window
(14) Firm Size	share price multiplied by common shares oustanding
(15) Book-to-market (1)	book equity in fiscal year t-1 divided by market equity at the end of December of year t-1 (following Fama and French (1993) definition)
(16) Liquidity Beta (1)	regression of firm returns in excess of the one-month Treasury bill rate on the Fama and French (1993) factors and aggregate liquidity using 60 months of data (following Pastor and Stambaugh (2003))

Table B.1 continued

Panel B. New financial variables

Variable Short Name	Variable Description
(17) Accruals (2)	change in operating working capital per split-adjusted share from fiscal year t-2 to t-1 divided by book equity per split-adjusted share at t-1. Operating working capital is defined as current assets minus cash and short term investments minus current liabilities plus debt in current liabilities (from Fama and French (2008))
(18) Age	number of years that a firm has been in the CRSP database (Baker and Wurgler (2006) definition)
(19) Analyst Coverage	number of analysts providing annual earnings forecasts on the I/B/E/S database
(20) Cash flow-to-market equity (2)	cash flow-to-market equity (updated monthly). Cash flow is defined as operating income after depreciation minus accruals
(21) Dividends-to-price (1)	total dividends paid from July of year t-1 to June of year t per dollar of equity in June of year t (Kenneth French online definition)
(22) Earnings-to-market equity (2)	Earnings divided by market equity. Earnings is defined as annual operating income after depreciation. Market equity is defined as price multiplied by common shares outstanding. This variable is updated monthly to reflect changes in market equity.
(23) Earnings-to-market equity (3)	Following Baker and Wurgler (2006), earnings is defined as income before extraordinary items plus income statement deferred taxes minus preferred dividends while market equity is as previously defined.
(24) External Finance (1)	change in assets minus the change in retained earnings all divided by total assets. Changes are calculated using 1 year of data following Baker Wurgler (2006) definition
(25) External Finance (2)	change in assets minus the change in retained earnings all divided by total assets. Changes are calculated using 5 years of data following Baker Wurgler (2006) definition
(26) Forecast Dispersion	standard deviation of analysts' annual earnings forecasts (from Diether et al. (2002))
(27) Intermediate Momentum	6 month cumulative compound return from 6 months prior (Novy-Marx (2012a) definition)
(28) Investments to Assets (2)	Capital Expenditures (CAPEX from COMPUSTAT) divided by lagged property, plant, and equipment (Avramov et al. (2012) definition)
(29) Investments to Assets (3)	Capital Expenditures (CAPEX from COMPUSTAT) divided by lagged property, plant, and equipment (Avramov et al. (2012) definition). Capital expenditures is calculated as the difference in total assets and total liabilities (Avramov et al. (2012) definition)
(30) Investments to Assets (4)	ratio between capital expenditures scaled by sales and the average capital expenditures over the prior 3 years minus one. Capital expenditures is defined as CAPEX from COMPUSTAT. This definition is from Titman et al. (2004).
(31) Investments to Assets (5)	ratio between capital expenditures scaled by sales and the average capital expenditures over the prior 3 years minus one. Capital expenditures is defined as the difference between total assets and total liabilities. This definition is from Titman et al. (2004).
(32) Liquidity Beta (2)	regression of firm returns in excess of the one-month Treasury bill rate on the Fama and French (1993) factors and aggregate liquidity using 12 months of data (following Pastor and Stambaugh (2003))
(33) Liquidity Beta (3)	regression of firm returns in excess of the one-month Treasury bill rate on the Fama and French (1993) factors and aggregate liquidity using 36 months of data (following Pastor and Stambaugh (2003))

Table B.1 continued

Panel B. New financial variables (continued)	
(34) Long-term Reversal (1)	24 month cumulative compound return
(35) Long-term Reversal (2)	36 month cumulative compound return
(36) Long-term Reversal (3)	48 month cumulative compound return
(37) Market Beta (2)	Market beta calculated using 12 months of data
(38) Momentum (2)	cumulative compound return from month t-6 to t-1
(39) Profit Margin	earnings before interest, taxes, depreciation, and amortization (EBITDA) divided by total revenue (REVT).
(40) PPE-to-Assets	total gross property, plant, and equipment divided by total assets (Baker and Wurgler (2006) definition)
(41) R&D-to-Assets	research and development expense divided by total assets (Baker and Wurgler (2006) definition
(42) Return Variance (8)	squared log 24 Month compound return
(43) Sales Growth (1)	1 Year sales growth using Baker and Wurgler (2006) definition
(44) Sales Growth (2)	5 Year sales growth using Baker and Wurgler (2006) definition
(45) Sales-to-market equity (1)	total revenues divided by market equity (calculated using market equity in June)
(46) Short-run momentum (1)	cumulative compound 3 month return
(47) Short-run momentum (2)	Lagged 1 month cumulative compound 3 month return
(48) Short-term Reversal	one month return at the time of formation
(49) SUE	SUE is defined as Standardized Unexpected Earnings, which is defined as the difference between current earnings and earnings four quarters ago divided by the standard deviation of this difference over the prior eight quarters (Chordia and Shivakumar (2006) definition)
(50) Unexpected Earnings (1)	difference between actual earnings reported in IBES and the median analysts' forecasted quarterly earnings divided by the share price at the end of the month prior to the earnings announcement (Livnat and Mendhall (2006) definition)

APPENDIX C

VARIABLE DESCRIPTIONS FROM CHAPTER 3

Accruals: Sloan (1996) finds that firms with low accruals outperform firms with high accruals. Following Sloan (1996), I define accruals as: Accruals = (ΔCA – ΔCash) - (ΔCL – ΔSTD –ΔTP) – Dep, where ΔCA is the change in current assets, ΔCash is the change in cash and equivalents, ΔCL is the change in current liabilities, ΔSTD is the change in debt included in current liabilities, ΔTP is the change in income taxes payable, and Dep is the depreciation and amortization expense. I construct the accruals measure using annual COMPUSTAT data.

Asset Growth: Cooper et al. (2008) found that firms with low asset growth outperform firms with high asset growth. Using the definition given in Cooper et al. (2008), asset growth is defined as the year over year change in total assets divided by lagged total assets.

Book-to-Market Ratio: Book-to-market ratio is defined as book equity for fiscal year *t-1* divided by market equity at the end of December of year *t-1*. Book equity is calculated as total assets minus total liabilities plus deferred taxes and investment tax credit minus preferred stock. Market equity is calculated as share price multiplied by common shares outstanding. I construct this measure following Fama and French (2008).

Daniel and Titman Composite: Daniel and Titman (2006) find a negative relation between composite share issuances and stock returns. Following their definition of composite share issuances, I define composite share issuances as

$$\iota(t-5,t) = \log\left(\frac{ME_t}{ME_{t-5}}\right) - r(t-5,t) \tag{21}$$

where ME_t is the firm's market equity today, ME_{t-5} is the firm's market equity 5 years ago, and $r(t\text{-}5,t)$ is this firm's 5-year log return.

Firm Size: Firm size is defined as price times shares outstanding, as in Fama and French (2008).

Gross Profitability: Gross profitability is defined as total revenue less cost of goods sold divided by total assets. This definition was used in Novy-Marx (2012).

Idiosyncratic Risk: I follow the methodology of Ang, Hodrick, Xing, and Zhang (2009) and calculate idiosyncratic risk as the standard deviation of the residuals from a monthly regression of daily excess returns on the Fama and French (1993) 3-factor model. Excess returns are calculated as the difference between firm returns and the risk-free rate, the 1-month Treasury bill rate.

Investments-to-assets: I use the definition of investments-to-assets given in Stambaugh et al. (2012). They define investments to assets as the annual change in gross property, plant, and equipment plus the annual change in inventories scaled by the lagged book value of assets.

Momentum: I define momentum as the compound return between months *t-12* and *t-2*. Jegadeesh and Titman (1993, 2001) provided evidence that firms with positive returns in the past continue to have positive returns in the short-term and firms with negative returns in the past continue to have negative returns in the short-term.

Net Stock Issuances: Net stock issuances is defined as the log ratio of split adjusted shares to lagged split adjusted shares following Fama and French (2008).

O-Score: I use the definition of Ohlson's (1980) O-score that was used in Chen, Novy-Marx, and Zhang (2011). Ohlson's O-score measures the probability of bankruptcy and is calculated using a variety of accounting measures including: total assets, book value of debt, working capital, net income, etc.

Persistence: Persistence is the institutional trade persistence measure from Dasgupta et al. (2011). This variable measures the number of (consecutive) quarters that a certain stock has been bought or sold by financial institutions. I construct this measure using 3 quarters of institutional holdings data.

Residual Institutional Ownership: Residual institutional ownership was previously used in Nagel (2005) to study short sales and stock returns. He defines residual institutional ownership as the residual ownership remaining after regressing logit institutional ownership on log firm size and squared log firm size. The goal of this measure is to capture the amount of institutional ownership that is unrelated to firm size. I construct residual institutional ownership following the methodology given in Nagel (2005).

Return on Assets: I calculate return on assets as income before extraordinary items divided by lagged total assets. Return on assets was previously used in Fama and French (2006) to study the relation between profitable firms and stock market returns.

Return on Equity: Return on equity is calculated as income before extraordinary items divided by lagged book equity. I calculate this variable following the definition given in Chen et al. (2011).

Share Turnover: Share turnover is calculated as the log of monthly share volume divided by common shares outstanding. This definition is similar to the definition used in Chordia et al. (2001).

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